Investigating the influence of firm size and industry differences on the R&D efficiency of firms

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Abstract
Organising the allocation of R&D subsidies in the most efficient manner has been and still remains challenging for governments. Currently, most US R&D funds or tax credits are targeted towards incumbents, under the assumption that larger firms are responsible for the majority of innovations. Even though larger firms are found to innovate more in absolute terms, most literature suggests that smaller firms are more efficient in transforming one additional R&D dollar into an innovation. Therefore, this study aspires to contribute to the existing literature by investigating how firm size moderates the effect of R&D expenditure on innovation performance, known as R&D efficiency. Secondly, this study analyses how industry differences affect firms' R&D efficiency. Third, this study examines how and why the moderating effect of firm size may be different depending on the industry a firm is operating in. By investigating these effects, this research aims to give more specific insights on what type of firms (regarding size and industry) are most efficient innovators. Ordinary Least Squares fixed effects regression analyses are conducted for a panel dataset consisting of 1644 publically-listed US firms over the period 1991-2010. The results show that firm size generally has a positive moderating effect on the relationship between R&D expenditure and innovation performance. The results also suggest that firms operating in Mark II industries are more R&D efficient compared to firms operating in Mark I industries. Lastly, a three-way moderation analysis does not find evidence that firm size has a positive and stronger moderating effect on the relationship between R&D expenditure and innovation performance for firms operating in Mark II compared to Mark I industries. Nonetheless, a split sample analysis shows that firm size positively and significantly moderates the effect of R&D expenditure on innovation performance for firms in Mark II industries, but not necessarily in Mark I industries. Thus, the relationship between firm size and R&D efficiency seems to differ depending on the industry and its varying technological regime characteristics. These findings may allow governments to allocate R&D subsidies more efficiently in order to stimulate higher levels of technological advancements, eventually leading to economic growth. Lastly, this study shows that this topic is a fruitful area to further explore for future research.

Keywords: R&D efficiency, R&D expenditure, innovation performance, patents, firm size, industries, Mark I, Mark II, technological regimes

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1. Introduction

Neoclassical economics has taught us that technological change leads to economic growth (Solow, 1956). Nobel laureate Robert Solow defined these technological improvements as 'improvements in business products or processes' and argues that these innovations positively affect economic growth. Over the years, economic literature has continued to place more focus on innovation. Economists have not only been challenged to identify the relevance and outcomes of innovation, but also the drivers. This research focuses on the latter.

Previous literature sees research and development (R&D) expenditure as one of the most important drivers leading to technological improvement, innovation and economic growth (Romer, 1990; Grossman & Helpman, 1991; Aghion & Howitt, 1992; Wang et al. 2007). Research suggests that R&D investments generally have a stronger social rate of return compared to the private rate of return (Leyden & Link, 1991; David et al., 2000). The societal benefit of R&D expenditures together with its positive contribution to innovation and economic growth provides governments the incentive to endorse R&D efforts through subsidies or other supporting policies (Cin et al., 2014). However, R&D efficiency (defined as the effectiveness of one additional R&D dollar of expenditure on innovation performance) differs when considering different firm and industry characteristics. This makes it challenging for governments to organise the allocation of R&D subsidies in the most efficient manner. Literature suggests that larger firms are more targeted and likely to use government R&D support, while smaller firms are significantly more able to produce innovations with R&D subsidies (Bérubé et al., 2009; Herrera et al., 2013). More specific findings concerning what type of firms use R&D most efficiently may give incentive to alterations in the allocation of federal R&D funds or tax credits. Apart from policy implications, a firm's level of R&D efficiency may also influence managerial decision-making with regard to their R&D expenditure. Therefore, this study analyses how the effect of R&D investment on innovation performance (R&D efficiency) differs across firm size and industries. The findings may provide a justification or advise an alteration of the US government's R&D policies and the firms' investment strategy according to their characteristics.

Until now, various scholars have researched the relationship between R&D expenditure and firm size (Schmookler, 1972; Cohen et al., 1987; Symeonidis 1996, Tsai et al., 2005), with some examining industry differences (Bound et al., 1984; Pavitt, 1984; Meliciani, 2000). Literature has also explored the relationship between innovation and firm size (Schumpeter, 1938, 1942; Panzar et al., 1981; Acs et al. 1991; Kim et al., 2009) with also some examining industry differences (Malerba et al., 1996; Breschi et al. 2000; Fontana et al., 2012). Studies have examined how R&D efficiency differs among firm sizes (Bound et al., 1984; Scherer et al., 1983a, 1983b; Hausman et al., 1984; Cohen et al., 1996; Herrera et al., 2013) while some have examined how R&D efficiency differs among industries (Taylor et al., 1973; Levin et al., 1987; Henderson et al., 1993; Bilbao-Osorio et al., 2004; Kim et al., 2009). Most literature above suggests that smaller firms are more R&D efficient compared to larger firms. Most literature also finds that firms in industries with high levels of cumulativeness, appropriability and technological opportunities are most R&D efficient. However, no study has yet explored the moderating effect of firm size and industries on the relationship between R&D expenditure and innovation performance, and how firm size effects the relationship differently among industries. Unprecedentedly, this research aims to find out whether and why in some industries, larger firms are more efficient innovators and in other industries, smaller firms are more efficient innovators. Therefore, this research contributes to the literature by aiming to formulate an answer to the following main research question:

Research question: *How is the relationship between R&D expenditure and innovation performance (R&D efficiency) influenced by firm size and its industry?*

This research aims to give more specific insights regarding what type of firms (regarding size and industry) are most efficient innovators. This study measures innovation performance as the number of successful patent applications. Even though it is often criticized to measure innovation using a form of patent count as key performance indicator, literature widely uses and accepts it as a comprehensive innovation indicator (Griliches, 1990; Nagaoka et al., 2010; Fagerberg, 2013). A Fixed Effects OLS regression model is used to conduct the analyses of a set of 1644 publicly listed US firms over the most recently available years 1991-2010. The use of recent data contributes to the scientific relevance of the research as most papers in the field have become out-dated due to their analyses of decennia-old firm financial and patent data. Therefore, the findings in this paper reflect recent trends allowing for more representative conclusions regarding the present market. In this study, firm size is defined as the number of employees. The 47 industries are aggregated into two categories, namely Schumpeter Mark I and Mark II industries that differ in technological regime conditions[1] (Breschi et al., 2000).

This research finds that, in general, firm size significantly strengthens the positive effect of R&D expenditure on innovation performance. This implies that larger firms are generally more R&D efficient compared to smaller firms. The findings also suggest that being in a Mark II industry strengthens the positive effect of R&D expenditure on innovation performance compared to being in a Mark I industry. This implies that firms in Mark II industries are generally more R&D efficient compared to firms in Mark I industries. Lastly, evidence does not find a significant three-way moderation effect of firm size having a positive and stronger moderating effect on the positive relationship between R&D expenditure and innovation performance in Mark II industries compared to Mark I industries. However, a split sample analysis does find that firm size significantly and positively moderates the effect of R&D expenditure on innovation performance for firms in Mark II industries, whilst the same or the contrary cannot be said for the Mark I sample due to insignificance. This seems to suggest that compared to smaller firms, larger firms are more efficient innovators in Mark II industries but not necessarily in Mark I industries. Thus, the relationship between firm size and R&D efficiency seems to differ depending on the industry and its varying technological regime characteristics.

The remainder of this paper is organized as follows. First, the theoretical framework describes the relevant literature regarding the relationship between R&D efficiency and firm size, R&D efficiency and Mark I and Mark II industries and how firm size moderates R&D efficiency differently for Mark I and Mark II industries. Here, the hypotheses are developed. Following, the data and methodology section explains how that data is structured, which models and variables are chosen, the descriptive statistics and the estimation strategy. Hereafter, the results are illustrated and interpreted. Furthermore, a robustness check is performed in order to check if the results hold when the variable of interest, firm size, is measured through sales instead of number of employees. A second robustness check is performed with the inclusion of a lagged R&D

[1] Schumpeter Mark 1 industry: Low appropriability, low cumulativeness, high technological opportunities, low generic knowledge, high specific knowledge. Schumpeter Mark II industry: High appropriability, high cumulativeness, low/high technological opportunities, high generic knowledge, low specific knowledge.

expenditure variable. Finally, a robustness check is performed using a Poisson fixed effects model. The discussion section contains the research findings, implications, limitations of the study and suggestions for further research. Lastly, the conclusion summarizes the main results and relevance of the research.

2. Theoretical framework

2.1. R&D expenditure & innovation performance: Firm size

Several widely acknowledged economists have found a positive relationship between R&D expenditure and innovation, where innovation is measured through patents (Hausman et al. 1984; Mansfield, 1984; Jaffe, 1986; Lerner & Wulf, 2007; Moser, 2016). This is because R&D investments lead to technological advancements, which lead to companies wanting to protect these innovations, thus more patent output. This yields similar results when observing the studies where specifically the number of patent applications is used as dependent variable (Bound et al., 1984; Pavitt, 1984; Jaffe, 1986; Meliciani, 2000; Bilbao-Osorio et al., 2004, Danguy et al., 2009). Due to this widely accepted consensus, this research assumes and also finds statistical evidence that R&D expenditure indeed has a significant positive effect on innovation performance.

Nevertheless, fewer studies have studied how firm size affects the relationship between R&D investment and innovation. In this research, the question concerns whether larger or smaller firms innovate more efficiently regarding their innovation return on R&D expenditure. In order to understand the potential variation in this relationship, it is relevant to consider two prominent views that shed light on the direct relationships between innovation and firm size, and R&D and firm size. Schumpeter identified two main patterns of innovation known as Mark I (Schumpeter, 1934) and Mark II (Schumpeter, 1942).

Mark I suggests that innovations come from small firms. It concerns 'creative destruction' and a 'widening pattern of innovation activities' meaning innovations are introduced by firms that did not innovate before. The innovative base is constantly increasing due to the entry of new firms and the technological and competitive advantages of established firms are impaired. There are low entry barriers and it centres around product innovations before the occurrence of a dominant design. In line with the Mark I view, various studies find that patent output from R&D investment falls as firm size increases (Bound et al., 1984; Hausman et al., 1984; Acs et al., 1991; Kim et al., 2009). Bound et al. (1984) explored the size-R&D relationship and subdivided a sample of US firms into two subgroups representing large and small firms (small being up to $10 million in sales). They found that small firms tend to patent more per R&D dollar than larger firms, thus are considered more efficient innovators. This is because, according to the U.S. Small Business Administration (1995), smaller firms performing R&D are relatively more research-intensive than larger firms, meaning they have a larger percentage of scientists and engineers. Compared to large firms, smaller firms seem to be able to transfer knowledge gained from external research associations more effectively, increasing their probability of applying for patents thus returns on R&D expenditure. Smaller firms focus more on providing solutions to critical problems affecting core areas of the business. Due to the scarcity of resources, they focus more on advancing core technologies and spend less on activities falling outside their core activity, enhancing their R&D efficiency (Corsten, 1987; Santoro et al., 2002). Lastly, smaller firms can adapt more rapidly to external changes and are more flexible, making them more interested in innovative activities which generate knowledge that can be applied to the market faster (Acs et al., 1990; Damanpour, 1996). For larger firms, innovations coming from R&D expenditure may take longer to become profitable because it takes more time to implement new knowledge (Herrera et al., 2013).

On the other hand, Mark II suggests that innovations come from large firms. It concerns ‘creative accumulation’ and a ‘deepening pattern of innovation activities’ meaning innovations are introduced by firms that innovated before. Here, few firms constantly innovate through the over time accumulation of innovative and technological capabilities. There are high entry barriers and it centres around process innovations after the occurrence of a dominant design (Malerba et al., 1996; Breschi et al., 2000). In this perspective, Schumpeter argues that larger firms have more market share and power, allowing them to capture returns to innovation and giving them an R&D advantage in terms of appropriability. In line with this view, various literature suggests that large firms conduct more R&D because they can better exploit unexpected innovations if they have multiple product lines, they can benefit from economies of scale (lower fixed costs to launch an R&D effort), they have better access to external financial sources, and have the ability to spread costs (Schumpeter, 1942; Panzar et al., 1981; Cohen et al., 1996). These findings supporting Mark II indeed suggest that large firms conduct more R&D, however this does not necessarily imply that they also conduct more patents per R&D dollar compared to small firms, thus are more efficient innovators.

Cohen et al. (1996) argue that larger firms have conducted and are more likely to conduct R&D compared to small firms because R&D is generally a fixed cost, where the net returns of R&D are higher the larger the level of output over which the costs can be spread. However, they also find that after many decades of study, evidence points in the same direction, namely that large firms do not possess an advantage regarding R&D efficiency. They suggest that innovative output increases less than proportionately with R&D, meaning the marginal efficiency of R&D is diminishing. This lower efficiency is not necessarily a disadvantage to large firms as it is a result of conducting more R&D to increase net returns made possible by cost spreading. As a result and contrary to Schumpeter Mark II (thus supporting Mark I), they illustrate the stylised fact that the number of patents per R&D dollar decreases with firm size and/or the level of R&D, and that smaller firms account for a disproportionately larger number of patents relative to their size.

Considering both views, most evidence points out that an increase in R&D expenditure has a proportionately larger significant positive effect on innovation (patent count) for smaller firms compared to larger firms. Even though most literature presents the common consensus that small firms carry this advantage, some scholars find varying results. From a survey, Symeonidis (1996) finds no relationship between size and R&D efficiency. Tsai et al. (2005) finds that both the smallest and largest firms have higher R&D efficiency.

Contrary to the literature that observes different sub-samples for small and large firms (Bound et al., 1984; Tsai et al., 2005), this research uses interaction terms to examine the extent to whether firm size leads to a stronger or weaker relationship between R&D expenditure and innovation performance. Despite the somewhat varying results, the following hypothesis is structured according to the findings from the majority of the literature.

H1: Firm size negatively moderates the positive relationship between R&D expenditure and innovation performance.

Apart from differences in firm size, literature also suggests that industry-specific characteristics influence the relationship between R&D expenditure and innovation performance. The following section, 2.2, is devoted to these industry differences.

2.2. R&D expenditure & innovation performance: Mark I & Mark II industries

The first hypothesis concerns the relationship between R&D expenditure and innovation performance and whether this effect is stronger for smaller or larger firms, without considering industry differences. However, not only does firm size influence the relationship, the type of industry and its characteristics also influence a firm's R&D efficiency (Dasgupta et al., 1980). This section explores how industry differences, identified as technological regimes, are related to firms' R&D efficiency. Following, the relationship between technological regimes and Mark I and Mark II industries are investigated. Shedding light on the relationship between technological regimes and Mark I and II is important in order to understand why the effect of R&D expenditure on innovation performance may differ per industry.

Winter (1984) argues that differences in industry characteristics can be distinguished through their technological regimes, which represent a particular knowledge environment where firm problem-solving activities occur. Breschi et al. (2000) define elements of the technological regimes as the appropriability of innovations, cumulativeness of technical advances, technological opportunities and properties of the knowledge base. These elements may serve as explanation that the incentives of firms to patent and that the relationship between R&D investment and innovation performance (R&D efficiency) differ per industry.

The first element of the technological regime is appropriability of innovations, defined as the successfulness to reap profits from innovative activities and protect innovations from imitations (Breschi et al, 2000). Pavitt (1984) suggests that appropriability conditions have led to sectoral differences regarding the efficiency of innovators. High appropriability increases the incentive to patent and innovate, which increases R&D expenditure because each dollar spent on R&D has a higher probability of turning into an innovation compared to an industry with low appropriability conditions (Levin, 1988). Therefore, firms in industries characterised by high appropriability tend to have higher R&D efficiency. However, it is important to consider that the role of patents in ensuring appropriability differs considerably per industry and that patents are not regarded as an essential incentive for innovation in all industries (Taylor et al., 1973; Levin, 1987). For example, Taylor et al. (1973) finds that without patent protection (allowing for appropriability), most R&D in the chemical and pharmaceutical sectors would not be undertaken but for the electronics and mechanical engineering industries this does not hold. Therefore, in industries where patents are less important, appropriability conditions may not necessarily be related to firms' R&D efficiency.

Secondly, the cumulativeness of technical advances occurs when innovations create new knowledge used for other innovations in related areas or generate a set of subsequent innovations, which are gradual improvements on the original one (Breschi et al., 2000). Industries with high cumulativeness of technological advances are characterised by increasing returns and continuities in innovative activities where innovative firms are more likely to innovate in the future along specific trajectories compared to non-innovative firms. Therefore, high cumulativeness leads to a higher concentration of innovative activities (Breschi et al., 2000). Cumulativeness in the form of gradual improvements on previous innovation are also known as incremental innovations, whereas radical innovations are completely new. More input (R&D expenditure) is generally required to successfully commercialise a radical innovation compared to an incremental innovation. This is because an incremental innovation relates to an existing market and technology, while a radical innovation relates to a new market and technology, increasing exploration and start-up costs (Ettlie et al., 1984; Revilla et al., 2012). Therefore, if an industry contains high cumulativeness, the cost of the innovation tends to be lower, meaning a one-dollar increase in R&D expenditure has a larger effect on innovation performance compared to an industry with low cumulativeness of technical advances. Therefore, firms in industries with high cumulativeness of technical advances may indicate higher R&D efficiency.

The third element is technological opportunities, which indicates the range of possible technical solutions to firm problem-solving activities and how easy such solutions can be achieved

(Marsili, 1999). High opportunities suggest that there are more innovations to be exploited compared to industries with low technological opportunities, stimulating innovative activity in these industries (Breschi et al., 2000). On the one hand, it is expected that a one-dollar increase in R&D has a larger effect on innovation (patent count) for firms in industries characterised by high technological opportunities. This is because more technological opportunities increases the probability of an opportunity being exploited and turned into an innovation. On the other hand, an industry with lower technological opportunities attracts less new entrants meaning firms already established in such an industry have less competition for the exploitation of opportunities and turning them into innovations (Marsili, 1999). Therefore, it is not possible to provide a general conclusion whether firms in industries with high or low technological opportunities are more efficient innovators, as it depends on the competition.

Lastly, the properties of the knowledge base in an industry also underpin a firm's innovative activities. According to Winter (1987), technological knowledge differs per industry among tacitness, complexity, specificity and independence. Breschi et al. (2000) refers to two sorts of knowledge: generic and specific knowledge. Generic knowledge is generated through basic sciences and refers to knowledge related to biology, chemistry, physics and mathematics. Specific knowledge is generated through applied sciences that respond more to problems generated by practical experience. The fields related to applied sciences are: medical & health, chemical engineering, mechanical engineering, electrical engineering, materials science and computing science. Currently, no studies have shown whether firms in industries characterised by generic or specific knowledge are more efficient innovators. Reason for this could be because it partly depends on the industry's source of the knowledge, for example universities, users, suppliers (Castellacci, 2008). Table 1 summarizes the relationship between the elements of the technological regime and a firm's R&D efficiency.

Table 1: The relationship between elements of the technological regime and R&D efficiency

	Elements of the technological regime				
	Appropriability	**Cumulativeness**	**Technological opportunities**	**Generic knowledge**	**Specific knowledge**
R&D efficiency (The effect of R&D expenditure on innovation performance)	+	+	+/-	+/-	+/-

Interestingly, Breschi et al. (2000) finds significant relationships between Mark I and Mark II and these elements of the technological regime. Shedding light on the relationship between Mark I and Mark II industries and how they differ among technological regime, can provide argumentation as to why firms in Mark I or Mark II are more R&D efficient. Mark I industries have low concentration of innovative activities, high relevance of new innovators and low stability in the hierarchy of innovators (Schumpeter, 1938). Mark II industries are characterised by high concentration of innovative activities, low relevance of new innovators and high stability in the hierarchy of innovators (Schumpeter, 1942). Breschi et al. (2000) find that sectors (in UK, Italy & Germany) characterised by low degree of appropriability and cumulativeness, an increasing role in external sources of knowledge and a high importance of specific knowledge are characterised by Mark I. Sectors characterised by high degrees of appropriability and cumulativeness, low importance of specific knowledge and high importance of generic knowledge as sources of innovation are related to Mark II. Table 2 summarizes the relationship between the technological regime and Mark I and Mark II.

Table 2: Technological regime elements related to Mark I and Mark II, Breschi et al. (2000)

	Elements of the technological regime				
	Appropriability	**Cumulativeness**	**Technological opportunities**	**Generic knowledge**	**Specific knowledge**
Mark I	Low	Low	High	Low	High
Mark II	High	High	Low/High	High	Low

Breschi et al. (2000) find that technological opportunities may be high or low for Mark II. It can be low in Mark II industries as a dominant design established by incumbents may restrict competition and the evolution of radical innovations due to entry barriers. It can be high for Mark II as it may increase the innovative advantage of established firms that cumulatively innovate upon past successes (Marsili, 1999). Schumpeter characterises industries in Mark I as having high technological opportunities because it is easier for new firms to attempt something that the incumbents have not tried yet, increasing entry and reducing market concentration.

Regarding the above, evidence suggests that especially appropriability and cumulativeness contribute to the R&D efficiency of firms (Ettlie et al., 1984; Levin, 1988; Revilla et al., 2012). Knowing that Mark II is characterised by high appropriability and cumulativeness as opposed to Mark I (Breschi et al. 2000), presents the implication that firms in industries characterised by Mark II are more efficient innovators, where the effect of R&D expenditure on patent output is generally stronger. Even though no literature has specifically researched how firms in industries characterised by either Mark I or Mark II patterns differ in efficiencies regarding the effect of R&D expenditure on innovation performance, some scholars provide support for this implication.

Cohen et al. (1996) states that if an industry has a higher concentration ratio (Mark II trait), this would reduce duplicative R&D and shift R&D spending to new projects increasing the industry's rate of technological progress and enhancing R&D efficiency. Further evidence suggests that R&D expenditures are found to be more effective in generating patents in technological and science-based industries (Bound et al., 1984; Pavitt, 1984; Meliciani, 2000), which tend to be Mark II (Breschi et al., 2000, Fontana et al. 2012). They argue that this is because these industries contain higher appropriability conditions and technological opportunities, increasing the propensity to patent. Fontana et al. (2012) find a positive relationship between cumulativeness in a given sector and the probability of breakthrough inventions, supporting the perspective that firms in Mark II industries are more efficient innovators. On the other hand, they find that the probability of breakthrough inventions in sectors become lower as the relevant knowledge becomes more concentrated across firms (Mark II trait). Even though their research is not specifically targeted towards R&D efficiency, a higher occurrence of breakthrough inventions does imply a more effective innovation performance, assuming that breakthrough inventions contribute more to innovation.

All in all, literature suggests that the differences in industry technological regimes as well as in the traits of Mark I and Mark II (concentration, stability and hierarchy) are likely to affect the ability and importance of patenting, firms' incentives in R&D expenditure, and the degree to which R&D expenditure is effective in contributing to innovation. As most literature supports, it is expected that the positive effect of R&D expenditure on innovation performance is larger for firms in Mark II industries compared to Mark I. This is because firms in Mark II industries generally have better appropriability conditions, high cumulativeness, and a high degree of technological opportunities (Cohen et al., 1996; Breschi et al. 2000; Fontana et al., 2012). Therefore, the hypothesis is structured as the following:

H2: Being in a Mark II industry positively moderates the positive relationship between R&D expenditure and innovation performance, compared to being in a Mark I industry.

2.3. R&D expenditure & innovation performance: Firm size in Mark I & Mark II industries

Building on H1 and H2, H3 examines how firm size affects the relationship between R&D expenditure on innovation performance differently for Mark I and Mark II industries. H1 hypothesises that an increase in firm size negatively affects the relationship between R&D expenditure on innovation performance. Therefore, it is expected that smaller firms are most efficient innovators regarding their R&D expenditure. H2 hypothesises that there is a stronger positive effect of R&D expenditure on innovation performance for firms in Mark II industries compared to firms in Mark I industries. Therefore, it is expected that firms in Mark II industries are more efficient innovators regarding their R&D expenditure. However, does this then imply that small firms in Mark II industries are the most efficient innovators? Or, does the effect of firm size on R&D efficiency depend on the industry and its Mark I and Mark II related technological regime conditions? In search of what type of firms are most efficient innovators, it is important to investigate whether and how the effect of firm size on R&D efficiency differs per industry.

Mark I industries follow an entrepreneurial regime and Mark II industries a routinized regime (Marsili, 1999). Schumpeter argues that in Mark I industries, small firms innovate more compared to large firms. Regarding R&D efficiency, most evidence suggests that an increase in R&D expenditure has a larger positive effect on innovation performance for smaller firms compared to larger firms (Bound et al., 1984; Hausman et al., 1984; Acs et al., 1991; Kim et al., 2009). Reason for this may be because in Mark I industries the technology regime conditions of low cumulativeness, low appropriability, high technological opportunities and high specific knowledge favour smaller firms compared to larger firms (Breschi et al., 2000). On the other hand, the technological regime conditions in Mark II industries (e.g. high cumulativeness & high appropriability) favour larger firms, implying that large firms may be more R&D efficient in Mark II industries compared to small firms (Schumpeter, 1942; Cohen et al., 1996; Breschi et al. 2000; Fontana et al., 2012). Some scholars find evidence supporting this.

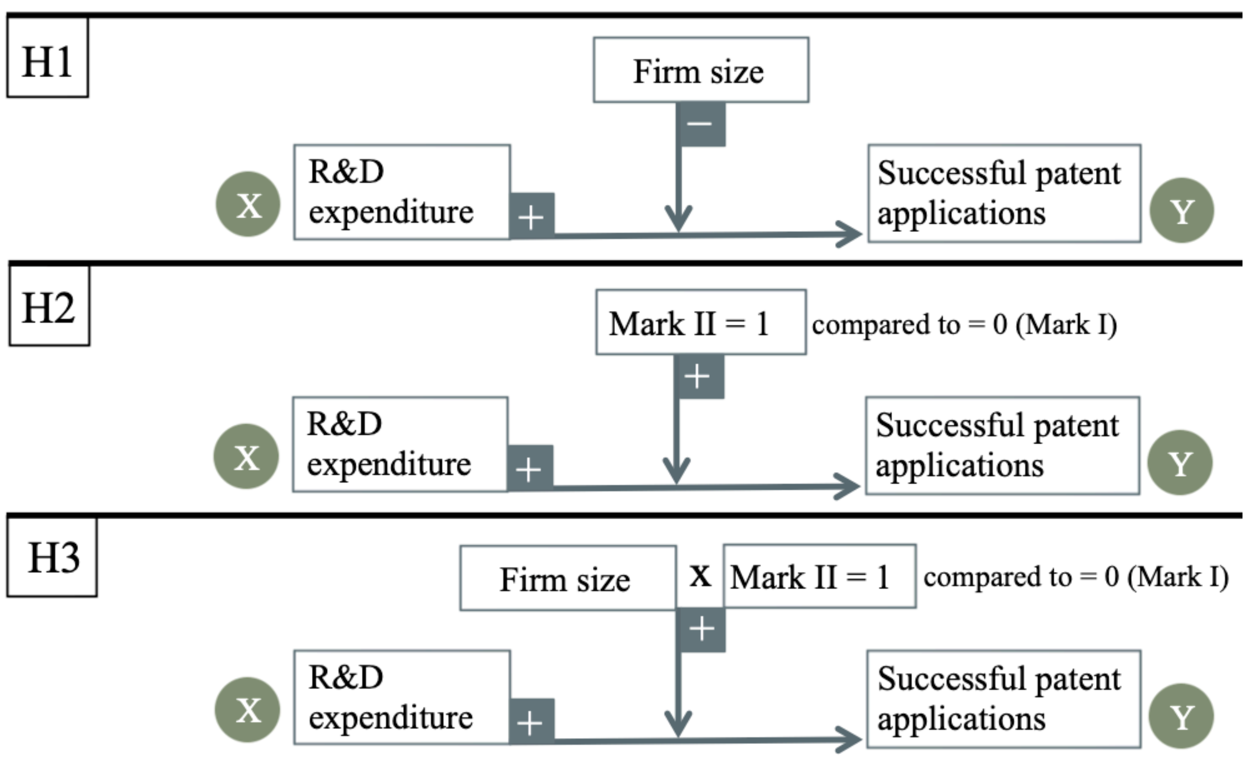
Schmookler (1972) analyses the amount of patents per R&D by firm size for six industrial sectors: machinery, chemicals, electrical equipment, petroleum, instruments, and all other industries, using 1953 US data. For all sectors, they find that the ratio is smallest for the largest firms, suggesting that smaller firms are more efficient in conducting innovation output per R&D expenditure. This effect is less present in the Mark II industries 'electrical equipment' and 'petroleum' and more present in the Mark I industries 'instruments' and 'machinery industries' (Table 5; Breschi et al., 2000; Fontana et al., 2012). Henderson et al. (1993) investigate the relationship between R&D expenditure and patents for the discovery of new drugs in the pharmaceutical industry over a 30-year period. This industry is known for having high appropriability conditions, high R&D intensities, and great technological opportunities (Mark II characteristics). They find evidence that R&D expenditure is more efficient in obtaining patents for larger firms, but that the relationship is somewhat U-shaped. Therefore, they suggest that the economies of scope and scale are effective for the discovery of new drugs up to a certain point. On the other hand, Kim et al. (2009) find that patents per R&D dollar decline with firm size for the semiconductor and pharmaceutical industries. Bound et al. (1984) find that smaller firms in machinery industries, a Mark I industry (Table 5), generate more patents per R&D dollar. Symeonidis (1996) finds that larger firms are important innovators in industries regarding food products, chemicals, metals, electrical engineering, and aerospace (mostly related to Mark II, Table 5) and smaller firms in machinery, instruments and construction (mostly related to Mark I, Table 5). Mansfield (1986) finds a statistically significant and positive correlation between firm size and the amount of patented innovations in the sectors where patents seemed most important: pharmaceutical, chemicals and petroleum (mostly Mark II, Table 5).

Overall, the theory and literature discussed may imply that there is a stronger positive effect of R&D expenditure on innovation performance for smaller firms compared to larger firms in Mark I industries. Interestingly, for Mark II industries it suggests that R&D efficiency is stronger for larger firms compared to smaller firms. This could imply that firm size positively moderates the effect of R&D expenditure on innovation performance for Mark II industries, compared to Mark I industries. Therefore, the following hypothesis is conducted in order to test whether firm size moderates differently among Mark I and Mark II industries:

H3: Firm size has a positive and stronger moderating effect on the positive relationship between R&D expenditure and innovation performance for firms operating in Mark II compared to Mark I industries.

To summarize, Figure 1 illustrates an overview of the expected relationships that have been outlined above.

Figure 1: Conceptual framework of expected results



H1 contains an interaction between R&D expenditure and firm size. H2 contains an interaction between R&D expenditure and being in a Mark II industry as apposed to Mark I industry (dummy). H3 contains a triple interaction between R&D expenditure, firm size and being in a Mark II industry as apposed to Mark I industry.

3. Data and methodology

3.1. Data

The data on patent applications for US publicly listed firms originates from the United States Patent and Trademark Office (USPTO) and is gathered from the National Bureau of Economic Research (NBER). The firm financial data used for collection of R&D expenditure originates from Compustat and is gathered from Bureau van Dijk. The merged dataset as described in Bhaskarabhatla et al. (2017) is used and has been made available by the authors on behalf of the Erasmus University Rotterdam.

The file is defined at the inventor (i) – firm (j) – patent level, where each patent is assigned to a given year. For this research, it is necessary to transform the dataset from patent level into firm level. A 20-year period between 1991-2010 is explored. This period is chosen as it has not been explored in this context before and because these are the most recent years available. All firms in the data have at least one successful patent application over the period, have recorded financial and patent data for at least three years, have non-negative R&D expenditure and sales values and have at least one employee. The years outside of this period are dropped, as are certain industry outliers that do not relate to the correct NAICS codes (North American Industry Classification System). As a result, the observed data contains 1644 firms with 14884 observations giving an average of approximately nine years of observations per firm. Each observation observes the relationships of the variables of interest for a firm (j) in a given year (t). Each firm is categorized in one of 47 three-digit NAICS industries present in the sample. Table 3 in the appendix includes the list of industry names and the amount of observations and firms per industry.

The dataset is structured as longitudinal panel data where each observation is time-unit. The ID variable *firmid* is defined by the firms' CUSIP6 code (Committee on Uniform Security Identification Procedures six-digit code). The time variable unit is *years*. It is an unbalanced dataset with gaps, however this may not necessarily present biased estimations as the Missing Completely at Random (MCAR) assumption is likely to hold. Nonetheless, a test for attrition is conducted to analyse whether the unequal loss may result in a systematic error.

3.2. Methodology

In this study, several models are estimated in order to identify how the relationship between R&D expenditure and innovation performance is influenced by the size of the firm and its industry. The econometric models related to each of the hypotheses are illustrated as follows[2].

Equation 1: General model

$$Log\left(Number\ of\ successful\ patent\ applications_{i,t} - \overline{Number\ of\ successful\ patent\ applications}_{i,t}\right) = \beta_0 + \beta_1 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) + \beta_2 Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) + \beta_3 Log\left(Age_{i,t} - \overline{Age}_{i,t}\right) + \beta_4\left(Profit\ Margin_{i,t} - \overline{Profit\ Margin}_{i,t}\right) + \beta_5\left(Years_{i,t} - \overline{Years}_{i,t}\right) + u_{i,t}$$

Equation 2: Hypothesis 1

$$Log\left(Number\ of\ successful\ patent\ applications_{i,t} - \overline{Number\ of\ successful\ patent\ applications}_{i,t}\right) = \beta_0 + \beta_1 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) + \beta_2 Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) + \beta_3 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) * Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) + \beta_4 Log\left(Age_{i,t} - \overline{Age}_{i,t}\right) + \beta_5 Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) + \beta_6\left(Profit\ Margin_{i,t} - \overline{Profit\ Margin}_{i,t}\right) + \beta_7\left(Years_{i,t} - \overline{Years}_{i,t}\right) + u_{i,t}$$

Equation 3: Hypothesis 2

$$Log\left(Number\ of\ successful\ patent\ applications_{i,t} - \overline{Number\ of\ successful\ patent\ applications}_{i,t}\right) = \beta_0 + \beta_1 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) + \beta_2\left(Mark\ II_{i,t} - \overline{Mark\ II}_{i,t}\right) + \beta_3 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) * \left(Mark\ II_{i,t} - \overline{Mark\ II}_{i,t}\right) + \beta_4 Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) + \beta_5 Log\left(Age_{i,t} - \overline{Age}_{i,t}\right) + \beta_6\left(Profit\ Margin_{i,t} - \overline{Profit\ Margin}_{i,t}\right) + \beta_7\left(Years_{i,t} - \overline{Years}_{i,t}\right) + u_{i,t}$$

Equation 4: Hypothesis 3

$$Log\left(Number\ of\ successful\ patent\ applications_{i,t} - \overline{Number\ of\ successful\ patent\ applications}_{i,t}\right) = \beta_0 + \beta_1 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) + \beta_2 Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) + \beta_3\left(Mark\ II_{i,t} - \overline{Mark\ II}_{i,t}\right) + \beta_4 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) * Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) * \left(Mark\ II_{i,t} - \overline{Mark\ II}_{i,t}\right) + \beta_5 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) * Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) + \beta_6 Log\left(R\&D\ expenditure_{i,t} - \overline{R\&D\ expenditure}_{i,t}\right) * \left(Mark\ II_{i,t} - \overline{Mark\ II}_{i,t}\right) + \beta_7 Log\left(\#Employees_{i,t} - \overline{\#Employees}_{i,t}\right) * \left(Mark\ II_{i,t} - \overline{Mark\ II}_{i,t}\right) + \beta_8 Log\left(Age_{i,t} - \overline{Age}_{i,t}\right) + \beta_9\left(Profit\ Margin_{i,t} - \overline{Profit\ Margin}_{i,t}\right) + \beta_{10}\left(Years_{i,t} - \overline{Years}_{i,t}\right) + u_{i,t}$$

[2] *Mark II* is a dummy variable with value 1 or 0. Since a fixed effects model is used, the main effects of the dummy displayed in equation 3 and 4 are in fact omitted in the regressions. They stand in the equations solely for completeness.

3.2.1. Dependent variable

Fagerberg (2013) states that one of the most common approaches to measure innovation performance is through patent applications. Due to data objectivity and availability, patent count is seen as a comprehensive innovation indicator, thus widely accepted and used in the literature (Griliches, 1990; Nagaoka et al., 2010). Therefore, the variable 'successful patent applications' is chosen as the dependent variable and key performance indicator for innovation performance. It is defined as the number of successful, thus granted, patents applied for by firm (j) in application year (t). Taking into account the successfully granted patents, gives a better indication of an innovation, as the probability for the invention to become commercialised is greater. The count variable contains the value '0', thus the natural log + 1 is used in order for an OLS regression to be possible.

3.2.2. Independent variable

The independent variable is the amount of R&D expenditure in USD deflated to constant price levels. R&D expenditure is often made up of costs such as hiring R&D personnel or purchasing R&D equipment. Firms usually do R&D investments in order innovate, differentiate and maintain/enhance a competitive advantage. The goal is often to discover a new technology, which is patentable.

Generally, R&D expenditure has an affect on the amount of patent applications for the same year (Hall et al., 1986). However, certain successful patents applied for are the result R&D expenditures from past years (Pakes et al., 1980). According to Kondo (1999) and Meliciani (2000), it takes an average of 1-1.5 years for R&D expenditure to result in a filed patent. Therefore, the model should theoretically include lagged R&D variables to estimate the effect of R&D expenditure on successful patent applications for the same and previous years. However, adding R&D expenditures from previous years may lead to multicollinearity concerns due to its high correlation with current R&D expenditures. To illustrate, the correlation between R&D expenditure and R&D expenditure t-1 is 0.97. If this 1-year lagged variable is added to the model, the VIF values of the individual coefficients of R&D expenditure and R&D expenditure t-1 are above the thumb rule of 10, suggesting multicollinearity issues may be at hand. Without the lagged independent variable, all VIF values are below 3 (see Table 14 in the appendix). Thus, the main model does not contain a lagged R&D expenditure variable.

Nevertheless, the robustness check tests whether the results differ greatly with a 1-year lagged variable included in the model. Solely a 1-year lag is tested because adding more lagged R&D variables would eliminate a substantial amount of observations, reducing the accuracy of the model.

3.2.3. Variable of interest: Firm size

In this research, the variable 'firm size' is measured by a firm's number of employees (in thousands). It is a time-varying continuous variable of which the natural log is take in the model. A wide range of academic literature accepts the number of employees as an accurate measure for firm size (Schmookler, 1972; Pavitt et al., 1987; Acs et al., 1987; Symeonidis 1996; Dolfsma et al., 2014). An alternative variable that can be used is total sales (Bound et al, 1984; Lerner et al., 2007). As a robustness check, the analysis will also be conducted using this alternative variable.

3.2.4. Variable of interest: Mark I & Mark II classification

Classifying industries in Mark I and Mark II can be done in various ways. Most studies perform a principle component analysis in order to construct an indicator, $Schump_{jt}$, based on an industry's level of concentration, entry and stability (Breschi et al., 2000; Fontana et al., 2012). A negative value of the indicator represents a Mark I industry and positive value a Mark II industry. Secondly, an industry classification in Mark I and Mark II may also be done by observing an industry's technological regime, namely its degree of cumulativeness, appropriability, technological opportunities and basic & applied science (Marsili, 1999; Breschi et al., 2000). Unfortunately, this research does not contain the necessary data to conduct a classification according to either one of these methods. This calls for a more unconventional method of classifying the industries into Mark I and Mark II.

Breschi et al. (2000) and Fontana et al. (2012) actually do not classify each separate industry into Mark I and Mark II, but they classify the industry's overarching technological category. In this regard, this research first aggregates the industries into six overarching technological categories, known as HJT (Hall, Jaffe, Trajtenburg) categories. These technological categories are defined as Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, Mechanical and Others (Hall et al., 2001). Following, the classification of these technological categories into Mark I and Mark II is based on a comparison of Breschi's et al. (2000) and Fontana's et al. (2012) classification of their technological categories into Mark I and Mark II. The following elaborates the two steps taken to make the classification. These steps are illustrated in Figure 2.

The first step is to aggregate the 47 NAICS3 industries into the six HJT technological categories. In the dataset, all patents applied for by firms in each industry are assigned to a specific HJT technological category. This makes it possible to determine the mode (most common) technological category for all applied patents in each industry over the period 1991-2010. As a result, each industry carries a number between 1 and 6 representing the technological category it falls under. For example, NAICS3 code '517' represents the industry 'telecommunications' and most patent applications (mode) in this industry are in the technology category '2' representing Computers & Communications, thus it is assigned to this category. Table 3 in the appendix shows each industry with its NAICS3 code and its HJT technological category.

Step two concerns classifying the HJT technological categories into Mark I and Mark II. This is determined using the results of Breschi et al. (2000) and Fontana et al. (2012). Their results suggest that industries in the HJT categories Chemical, Computer & Communications, Drugs & Medical and Electrical & Electronic technological categories relate more to Mark II and that Mechanical and Others relate more to Mark I. Table 5 illustrates their results and Table 4 shows the HJT technological categories with its subclasses. In Table 4 (the left side), it can be observed that the subclasses of the first four HJT categories are 'blue' and are very similar to the categories Breschi et al. (2000) and Fontana et al. (2012), classified as Mark II in Table 5 (on the right side). The 'Mechanical' and 'Others' technological categories have 'green' coloured subclasses, as these relate more to what Breschi et al. (2000) and Fontana et al. (2012) describe as Mark I. For example, they find that 'mechanical electrical technologies' and 'transport' are Mark I, which are also identified as subclasses of the Mechanical HJT technological category (Hall et al., 2001). Therefore, the Mechanical HJT category is classified as Mark I. Essentially, the classification into Mark I and Mark II is based on how Breschi et al. (2000) and Fontana et al. (2012) previously classified Mark I and Mark II for slightly different technological categories (Table 5).

Table 4: HJT technological categories and their relation to Mark I and Mark II

	HJT tech. category subclasses	HJT tech. category
1	Agriculture, Food, Textiles Coating Gas Organic Compounds Resins Miscellaneous–chemical	**Chemicals**
2	Communications Computer Hardware & Software Computer Peripherals Information Storage Miscellaneous–Computers	**Computers & communications**
3	Drugs Surgery and Med instruments Biotechnology Miscellaneous–Drugs and Medicine	**Drugs & Medical**
4	Electrical Devices Electrical Lighting Measuring and Testing Nuclear and X-rays Power Systems Semiconductor Devices Miscellaneous–Electronic	**Electrical & electronic**
5	Material Processing and Handling Metal Working Motors and Engines + Parts Optics Transportation Miscellaneous–Mechanical	**Mechanical**
6	Agriculture, Husbandry, Food Amusement Devices Apparel and Textile Earth Working and Wells Furniture, House Fixtures Heating Pipes and Joints Receptacles Miscellaneous–Others	**Others**

HJT technological category number on the left side. The column in the middle shows the HJT technological category subclasses and are colored either blue or green depending on whether Breschi et al. (2000) and Fontana et al. (2012) has categorized it as Mark I or Mark II. The right column shows the HJT category name (Hall et al., 2001).

Table 5: Breschi et al. (2000) & Fontana et al. (2012) Mark I and Mark II classification

	Breschi et al. (2000)		**Fontana et al. (2012)**	
Mark I	Civil engineering Mechanical electrical technologies Mining Railways and ships Natural artificial fibers, paper Household electrical appliance Industrial machinery Medical preparations Measurement & control instruments	&	Process engineering	*Chemical Engineering Materials processing, textiles, paper Handling, printing Agricultural and food processing, machinery and apparatus Environmental technology*
			Mechanical engineering	*Machine tools Engines, pumps, turbines Thermal processes and apparatus Mechanical elements Transport Space technology, weapons*
Mark II	Organic chemicals Miscellaneous chemical compounds Macromolecular compounds Electronic components Gas, hydrocarbons, oil Agricultural chemicals Consumer electronics Engines, turbines, pumps Vehicles	&	Instruments	*Optics Analysis, measurement, control technology Medical technology Nuclear engineering*
			Electrical engineering	*Electrical machinery and apparatus, electrical energy Audio-visual technology Telecommunications Information Technology Semiconductors*
			Chemistry, pharmaceuticals	*Organic fine chemistry Macromolecular chemistry, polymers Pharmaceuticals, cosmetics Biotechnology Agriculture, food chemistry Chemical and petrol industry, basic materials chemistry Surface technology, coating Materials, metallurgy*

Mark I and Mark II consist of these technological categories according to Breschi et al. (2000) and Fontana et al. (2012). The HJT technological categories in table 4 can be classified into Mark I and Mark II when observing the similarities with Breschi et al. (2000) and Fontana et al. (2012) proven classification.

Figure 2: Industry classification into Mark I and Mark II (including step 1 and step 2)

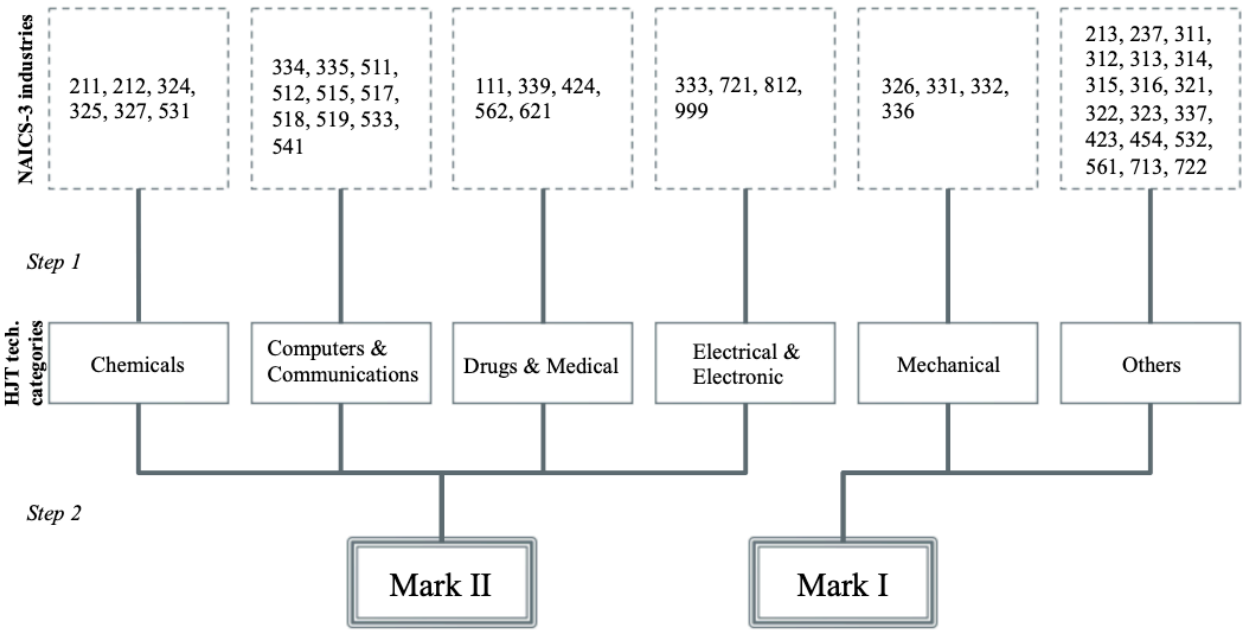


Figure 2 illustrates these two steps taken in order to classify the industries into Mark I and Mark II. All industries are classified in a HJT technological category, which is classified into Mark I and Mark II. This makes it possible to make a dummy variable where *Mark II* equals '1' if the industry is in the Chemical, Computer & Communications, Drugs & Medical or Electrical & Electronic HJT technological category. Similarly, *Mark I* equals '0' for industries in the Mechanical or Others HJT technological category. Using this dummy variable, the research tests whether being in a Mark II industry positively moderates the positive effect of R&D expenditure on innovation performance compared to being in a Mark I industry.

3.2.5. Control variables

Control variables are included in the regression in order to obtain a better approximation of the relationship between R&D expenditures and innovation performance. These covariates are expected to relate to the dependent and independent variable, thus taking them out of the equation limits the chances of omitted variable bias. Previous research has found that profitability, firm age, firm size and inter-industry differences are important to control for when exploring the effect of R&D expenditure and innovation performance (Bound et al., 1984; Cohen, 1996; Vossen, 1998; Scherer, 2001; Coad et al., 2016; Rafiq et al., 2016). According to

Simanjuntak et al. (2011), profitability has a significant positive effect on R&D expenditure. To control for this, the profit margins (ebitda/sales) are included in the model. Regarding age, Coad et al. (2016) find that younger firms undertake riskier innovations. They face greater innovation performance benefits if successful but greater losses if unsuccessful, compared to older firms. Therefore, the ages of the firms (in years) are in included in the model. Lastly, secular trends in the results are common across time. For example, an increase in the annual domestic inflation rate decreases R&D expenditure (Chu et al., 2015). This is controlled for by including year fixed effects estimations. Firm size needs to be controlled for in H2 as larger firms may patent more often simply because they are bigger and employ personnel such as patent lawyers only for this purpose (Bound et al., 1984). Lastly, like all time-invariant variables, industry fixed effects are automatically controlled for due to the inclusion of individual-firm fixed effects. Section 3.2.7. further elaborates on why individual-firm fixed effects are included.

3.2.6. Descriptive statistics

Table 6 displays descriptive statistics of the main variables. Coming from 1644 firms, there are 14884 observations that take part in the analysis. The table shows that the dependent count variable, number of successful patent applications, has a much larger variance than mean, suggesting it is severely overdispersed. This presents issues when wanting to use a Poisson model for count data, as Poisson assumes the mean is equal to the variance (Hausman et al., 1984). Therefore, the dependent variable is transformed into a natural logarithmic value to make OLS possible. This is elaborated on in the following section. The table also illustrates highly skewed distributions for most variables. In order to improve the distributions, a natural logarithmic transformation is taken for all variables except the industry dummy variable and profit margin (as it contains negative values).

Table 6: Descriptive statistics of relevant variables

Descriptive statistics	**Number of successful patent applications**	**R&D expenditure (thousands)**	**Mark II industry dummy**	**Number of employees (thousands)**	**Age (years)**	**Profit margin (ebitda/sales)**
Mean	115.98	292.68	.82	16.77	14.50	-6.88
Observations	14884	14884	14884	14884	14884	14884
Max	15738	14441.05	1	486	35	.93
Min	0	0	0	.001	3	-29325.70
SD	525.96	937.53	.38	42.05	8.56	291.36
se(mean)	4.31	7.69	.003	.35	.07	2.39
Skewness	12.51	5.87	-1.69	5.40	.54	-80.40
Variance	276634.50	878961.40	.15	1768.35	73.22	84892.77

Table 7 displays the correlations of the relevant variables. The number of successful patent applications is positively and significantly correlated with R&D expenditure, firm size (number of employees) and firm age. R&D expenditure is positively correlated firm size and firm age. Firm size is positively correlated with firm age and firm age is positively correlated with profit margin. Most of these correlations are not considered strong as the R-values are smaller than 0.70. The highest correlation with R-value 0.698 occurs between R&D expenditure and the number of employees. This seems logical as larger firms with more employees simply have more capital to spend on R&D.

Table 7: Correlation Matrix

Variables	**Number of successful patent applications**	**R&D expenditure (thousands)**	**Mark II industry dummy**	**Number of employees (thousands)**	**Age (years)**	**Profit margin (ebitda/sales)**
Number of successful patent applications	1.0000					
R&D expenditure (thousands)	0.5670*	1.0000				
Mark II industry dummy	0.0398*	-0.0094	1.0000			
Number of employees (thousands)	0.5560*	0.6980*	-0.1533*	1.0000		
Age (years)	0.1574*	0.1554*	-0.1937*	0.2213*	1.0000	
Profit margin (ebitda/ sales)	0.0050	0.0043	-0.0108	0.0095	0.0221*	1.0000

**p<0.05*

3.2.7. Estimation strategy

Count data models are often used to analyse the relationship between R&D expenditure and patents at firm level (Wang et al., 1998). A Poisson regression model is common as it takes into account that the dependent variable is a nonnegative count rather than continuous variable. However, the Poisson model may influence the results and lead to bias as it tends to give larger observations more weight compared to least squares on log patents (Bound et al., 1984). According to Hausman et al. (1984), the Poisson model is highly restrictive as it assumes the mean is equal to the variance. This presents an issue for this research as the dependent variable, amount of successful patent applications, contains severe overdispersion (variance>mean). This problem may be countered by estimating a negative binomial model, where the Poisson parameter is drawn from a gamma distribution. However, unlike with least squares, if the specific distribution is wrongly specified, the maximum likelihood estimates may be inconsistent (Wooldridge, 2012). Additionally, a negative binomial model does not work well with fixed effects, making it difficult to control for time-invariant characteristics (Allison et al., 2002). For this reason, and because of the high variation the dependent variable, an OLS model with log patents as the dependent variable is used for this research. According to Bound et al. (1984), an OLS considerably mitigates the problem of inconsistencies that occur due to the increasing variance of patents. Table 8 in the appendix shows the general models for the OLS model with the dependent variable 'log successful patent applications', and the Poisson and Negative Binomial model with the dependent count variable 'successful patent applications'. As expected, the magnitudes differ per model due to the different assumptions mentioned. However, the sign and significance of the independent variable are the same across all models. They consistently suggest a positive and significant effect of R&D expenditure on the amount of successful patent applications, which is in accordance with the literature (Bound et al., 1984; Pavitt, 1984; Jaffe, 1986; Meliciani, 2000; Bilbao-Osorio et al., 2004, Danguy et al., 2009).

Secondly, it is expected that a fixed effects OLS model is suitable to control for individual firm fixed effects and account for all (un)observed time-invariant characteristics (Hausman et al., 1984). Using only within-individual variation to estimate the parameters and averaging the estimates over the individuals (demeaning) allows for all stable covariates to be controlled for without actually including them in the equation. Results from a Hausman test show that there are systematic differences in the coefficients between the random effects and fixed effects estimator, suggesting that time invariant characteristics are indeed important. Therefore, a fixed effects estimator is preferred as the random effects estimator is found to be inconsistent and biased. The disadvantage of fixed effects is that time-variant variables such as industry dummies are not individually identified as they are encompassed by the individual firm fixed effects (Castellani et al., 2016). This, however, is not expected to present issues for this research.

Third, the OLS model is considered non-biased if certain assumptions hold. First, there should be sample variation. This is expected to hold as there is no perfect collinearity present in the model (no exact relationships among explanatory variables). The second is random sampling where a random sample of size n is used for the population of publicly listed US firms. Of course, if all firms in the US (incl. non publicly listed) are considered as the population, then the sample is not completely random as the firms in this sample already indicate a degree of size and success. Therefore, the conclusions in this research solely regard publicly listed US firms and may only give an indication of what could be an occurring trend for all US firms. Another assumption is homoscedasticity, implying that the variance of the errors should be constant. To control for potential heteroskedasticity, robust standard errors are included (Hayes et al., 2007). The panel dataset is unbalanced and contains gaps and including robust standard errors and clustering *firmid* allows for arbitrarily unbalanced panels. Lastly, the zero conditional mean assumption should hold, meaning the errors are uncorrelated with the explanatory variables. Because panel data is used, fixed effects are included to control for omitted variable bias by measuring changes within firms across time.

4. Results

The OLS fixed effects regression analyses have been performed to test the hypotheses and are displayed in Table 9. Figure 3 visualizes the results. The following subsections elaborate on the results per hypothesis.

4.1. General model

Even though literature finds a positive effect between R&D expenditure and innovation performance, it is important to validate this relationship for this research (Bound et al., 1984; Pavitt, 1984; Jaffe, 1986; Meliciani, 2000; Bilbao-Osorio et al., 2004, Danguy et al., 2009). Model 1 in Table 9 illustrates the general model without interactions. The results show that the independent variable, R&D expenditure, has a positive and significant effect on innovation performance (measured as the number of successful patent applications). To be exact, a 1% increase in R&D expenditure (USD deflated to constant price levels) increases the number of successful patent applications by 0.34%, ceteris paribus. This effect is significant at a 1% level.

Regarding the control variables, most show a result in line with the literature. As can be observed, firm size has a positive effect on innovation performance, significant at 1% level. This implies that the larger the firm, the higher the amount of successful patent applications. Despite the literature, firm age does not seem to have a significant effect on the number of patent applications in this model. As expected, the small but positive coefficients for the profit margin imply that a larger profit increases the number of successful patent applications, significant at 1% level. Lastly, the constants are non-interpretable as they are collinear with the fixed effects. The value of the constant depends on which identifying restriction is imposed to break that collinearity (in this case, xtreg fe).

4.2. Hypothesis 1: The moderating role of firm size

Hypothesis 1 tests the moderating role of firm size on the relationship between R&D expenditure and innovation performance (R&D efficiency). Model 2 in Table 9 displays the results for the regression.

The hypothesis states that firm size negatively moderates the positive relationship between R&D expenditure and innovation performance. This implies that firm size negatively effects on R&D efficiency. Surprisingly, the results show a positive moderation effect of firm size on R&D efficiency. This effect is significant at 5% level. Thus, an increase in firm size actually strengthens a firm's R&D efficiency, implying that larger firms are generally more efficient innovations compared to smaller firms. Therefore, hypothesis 1 is rejected.

4.3. Hypothesis 2: The moderating role of Mark I & Mark II

Hypothesis 2 tests the moderating role of industry differences (Mark I, Mark II) on the relationship between R&D expenditure and innovation performance (R&D efficiency). Model 3 of Table 9 displays the results for the regression. The dummy variable used to estimate this moderating role carries the value 1 for firms in Mark II industries and 0 for firms in a Mark I industries. The model does not contain a main effect for the dummy *Mark II* as it is time-invariant, thus omitted due to fixed effects. With fixed effects, a time-invariant dummy can only be included and interpreted when it interacts with a time-variant variable, in this case R&D expenditure (Wooldridge, 2012). This hypothesis tests whether the relationship between R&D expenditure and innovation performance depends on whether a firm is in a Mark I or Mark II industry, which can still be observed without an estimation of the main effect.

The hypothesis states that being in a Mark II industry strengthens the positive effect of R&D expenditure on innovation performance compared to being in a Mark I industry. The interaction term in model 3 confirms that being in a Mark II industry strengthens (positively moderates) the effect of R&D expenditure on the number of successful patent applications compared to being in a Mark I industry, ceteris paribus, significant at 5% level. Therefore, firms in Mark II industries resemble more efficient innovators compared to firms in Mark I industries. Thus, the findings are consistent with hypothesis 2.

A split sample analysis presented in Table 10 also finds a stronger effect of R&D expenditure on innovation performance for the sample of firms in Mark II industries compared to the sample of firms in Mark I industries. Model 1 shows that a 1% increase in R&D expenditure increases the number of successful patent applications by 0.32% for firms in Mark I industries, ceteris paribus, significant at 5% level. Model 2 shows that a 1% increase in R&D expenditure increases the number of successful patent applications by 0.50% for firms in Mark II, ceteris paribus, significant at 1% level. Thus, the R&D efficiency seems to differ per type of industry, whereas the results of the full sample and split sample analysis suggest that firms in Mark II industries are more R&D efficient compared to firms in Mark I industries.

4.4. Hypothesis 3: Differences in the moderating role of firm size for Mark I & Mark II

Hypotheses 3 tests how the moderation effect of firm size on the relationship between R&D expenditure and innovation performance differs among different types of industries, namely Mark I and Mark II (higher order moderator). Model 4 in Table 9 displays the results for the regression.

The hypothesis states that the moderation effect of firm size on the positive relationship between R&D expenditure and innovation performance is positive and stronger for firms operating in Mark II compared to Mark I industries. However, the three-way interaction term in model 4 does not show a significant effect. Thus, evidence does not suggest that firm size has a significantly stronger or weaker positive or negative moderation effect on R&D efficiency for firms operating in Mark II industries compared to Mark I industries. Therefore, hypothesis 3 can neither be accepted nor rejected.

However, the split sample analysis in table 10 shows a positive and significant interaction term between firm size and R&D expenditure for the sample of firms in Mark II industries (model 4). No significance is found for Mark I industries (model 3). This seems to suggest that firm size positively and significantly strengthens R&D efficiency in Mark II industries, but not necessarily in Mark I industries. Thus, an increase in firm size leads to higher R&D efficiency for firms in Mark II industries, whilst the same or the contrary cannot be said for firms in Mark I industries.

Therefore, in the Mark II sample, larger firms are found to be more R&D efficient compared to smaller firms. In the Mark I sample, an increase in firm size does not seem to significantly effect R&D efficiency.

Figure 4 illustrates the moderation effect of firm size on the relationship between R&D expenditure and innovation performance for Mark I and Mark II industries. For Mark II, the increasing line (red) indicates a positive interaction between the number of employees (firm size) and R&D expenditure on the number of successful patent applications (innovation performance). The 95% confidence interval consistently supports this positive relationship. This interaction effect is statistically significant at 1% level. For Mark I, the confidence intervals are much larger, which may be explained by the fact that Mark I only accounts for 18% of the sample observations. Here, the interaction effect is statistically insignificant at 10% level. Even though the line is slightly increasing, the insignificance and the confidence interval indicate that the moderating effect of firm size on R&D efficiency may be non-existent or even negative for firms in Mark I industries.

Overall, the three-way interaction suggests that firm size does not have a significantly different moderation effect on R&D efficiency for firms in Mark II industries compared to Mark I industries. However, the results in Table 10 may suggest that firm size effects R&D efficiency differently when observing the separate samples of Mark I and Mark II. This is because a significant positive effect is found for Mark II but no significance is found for Mark I industries. This shows that the firm size-R&D efficiency relationship may still differ among industries, where firm size may be of more importance in contributing to R&D efficiency in one industry compared to another.

4.5. Model comparison

As mentioned in section 3.2.7., using an OLS model for this research may not present the most accurate magnitudes. Previously, often-used models such as Poisson or Negative Binomial (for count dependent variable) are known to produce different magnitudes. Literature argues that choosing the best estimation model is and remains a challenge when analysing the R&D-patent relationship (Bound et al., 1984; Wang et al., 1998; Wooldridge, 2012). This implies cautious interpretation of the results. Nonetheless, the sign and significance usually tend to remain consistent.

In order to determine the explanatory power of the models, it is possible to observe the R-square value. The models in Table 9 show a rather consistent R-square value of approximately 0.11, meaning that 11% of the variation can be explained by the model's inputs and 89% by other omitted variables. In certain fields, such as social sciences, low R-square values often occur, because it is difficult to specify such models. Nevertheless, it is possible to generate a lot of data with a low R-square, as it is not expected that the models include all relevant predictors to explain an outcome. A small R-square can still be significantly different from 0, indicating that the model has statistically significant explanatory power (Paetzold, 2014). Overall, the models show minor differences in R-square values. Therefore, adding industry differences (Mark II dummy) does not seem to explain a great deal of the variance in R&D efficiency.

As mentioned, the panel dataset is unbalanced and contains gaps. This means that some firms are missing data in certain years, resulting in cases of a loss to follow-up. This unequal loss may result in a systematic error, known as attrition bias. In order to test whether the chosen fixed effect model suffers from attrition bias, a variable *nextwave* is created that is '1' if the sample equals '1' in the next wave and '0' if the value for that sample is missing in the next wave. The results are found in Table 15 in the appendix. The general model shows a positive and significant coefficient for *nextwave* (1% significance level). This indicates a concern for attrition bias where being in the next wave has a significant positive effect on the number of successful patent applications in the current wave. Most panel data suffer from attrition. Attrition bias does not automatically mean the estimates are biased, it merely weakens the internal and external validity meaning the study cannot be generalized to other populations (Schulz et al., 2002). Nonetheless, attrition bias should not be neglected when intepreting the results.

Table 9: OLS fixed effects regression with dependent variable Log 'number of successful patent applications' and 'number of employees' as a measure of firm size

VARIABLES	(1) General	(2) H1	(3) H2	(4) H3
Log (R&D)	0.462*** (0.043)	0.405*** (0.043)	0.291*** (0.097)	0.276** (0.126)
Log (# of Employees)	0.171*** (0.041)	0.064 (0.047)	0.157*** (0.041)	-0.009 (0.143)
Log (R&D) x Log (# of Employees)		0.039*** (0.012)		0.026 (0.040)
Mark II			-	-
Log (R&D) x Mark II			0.214** (0.104)	0.163 (0.135)
Log (# of Employees) x Mark II				0.055 (0.152)
Log (R&D) x (# of Employees) x Mark II				0.019 (0.042)
Log (Age)	0.096 (0.102)	0.121 (0.102)	0.075 (0.101)	0.096 (0.102)
Profit Margin	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Year Fixed Effects	YES	YES	YES	YES
Constant	0.395 (0.242)	0.408* (0.241)	0.425* (0.241)	0.473* (0.245)
Observations	14,884	14,884	14,884	14,884
R-squared	0.108	0.111	0.109	0.113
Number of Firms	1,644	1,644	1,644	1,644

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These OLS fixed effects models control for individual-firm fixed effects. The fixed effects function accounts for time-invariant characteristics such as industry fixed effects (in the sample, firms do not change from industry over time), thus these are automatically controlled for in the model. There is no main effect present for the dummy variable *MarkII* as fixed effects cannot estimate a coefficient for time-invariant variables. However, this does not present issues regarding the interpretation of the interaction terms. By adding year fixed effects, all models control for potential secular trends over time. Lastly, standard errors equal to zero are obviously highly suspicious, therefore it is important to note that the coefficients and standard errors for *Profit Margin* are not equal to zero but too small to be visual at 3 decimals.

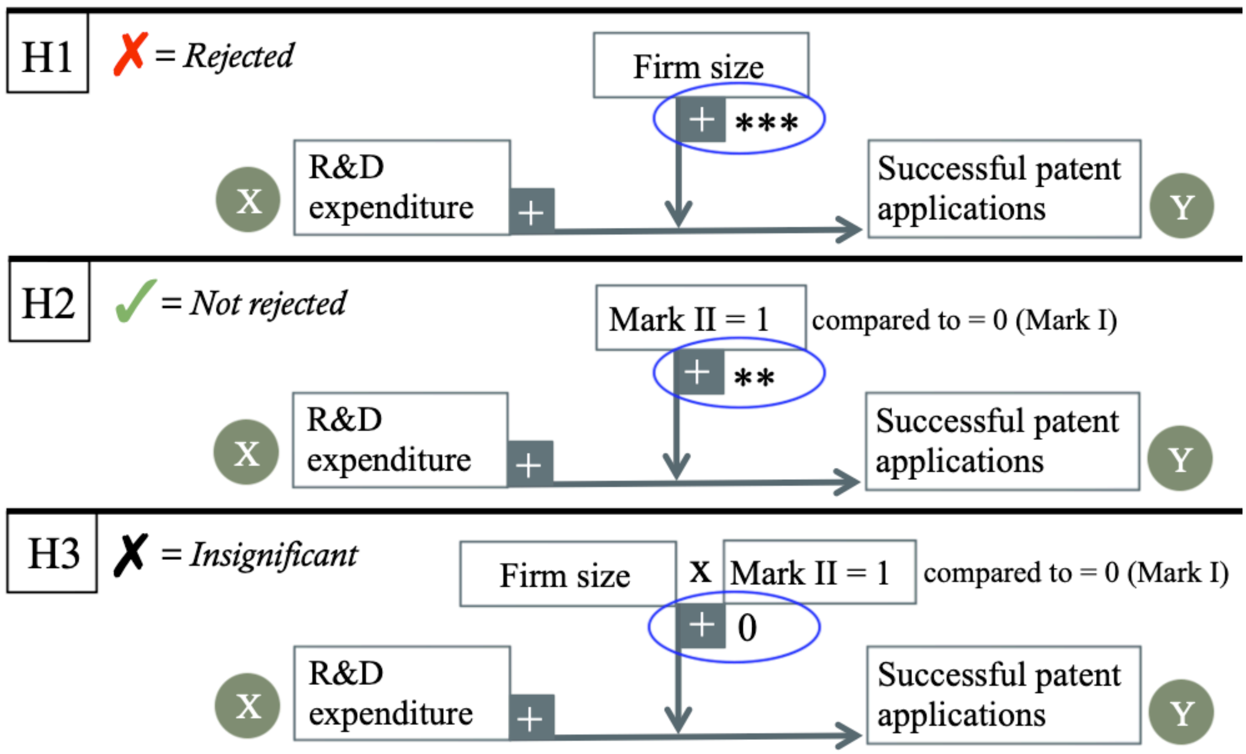
Table 10: Split sample OLS fixed effects regressions for Mark I and Mark II industries with dependent variable Log 'number of successful patent applications'

	H2		H3	
VARIABLES	(1) Mark I	(2) Mark II	(3) Mark I	(4) Mark II
Log (R&D)	0.319*** (0.099)	0.496*** (0.047)	0.261** (0.123)	0.439*** (0.046)
Log (# of Employees)	0.091 (0.128)	0.169*** (0.044)	0.011 (0.149)	0.044 (0.050)
Log (R&D) x Log (# of Employees)			0.026 (0.041)	0.045*** (0.012)
Log (Age)	0.029 (0.326)	0.087 (0.109)	0.059 (0.331)	0.112 (0.110)
Profit Margin	-0.002*** (0.001)	0.000*** (0.000)	-0.002*** (0.001)	0.000*** (0.000)
Year Fixed Effects	YES	YES	YES	YES
Constant	0.792 (0.855)	0.389 (0.260)	0.827 (0.852)	0.393 (0.257)
Observations	2,643	12,241	2,643	12,241
R-squared	0.051	0.123	0.052	0.128
Number of Firms	254	1,390	254	1,390

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

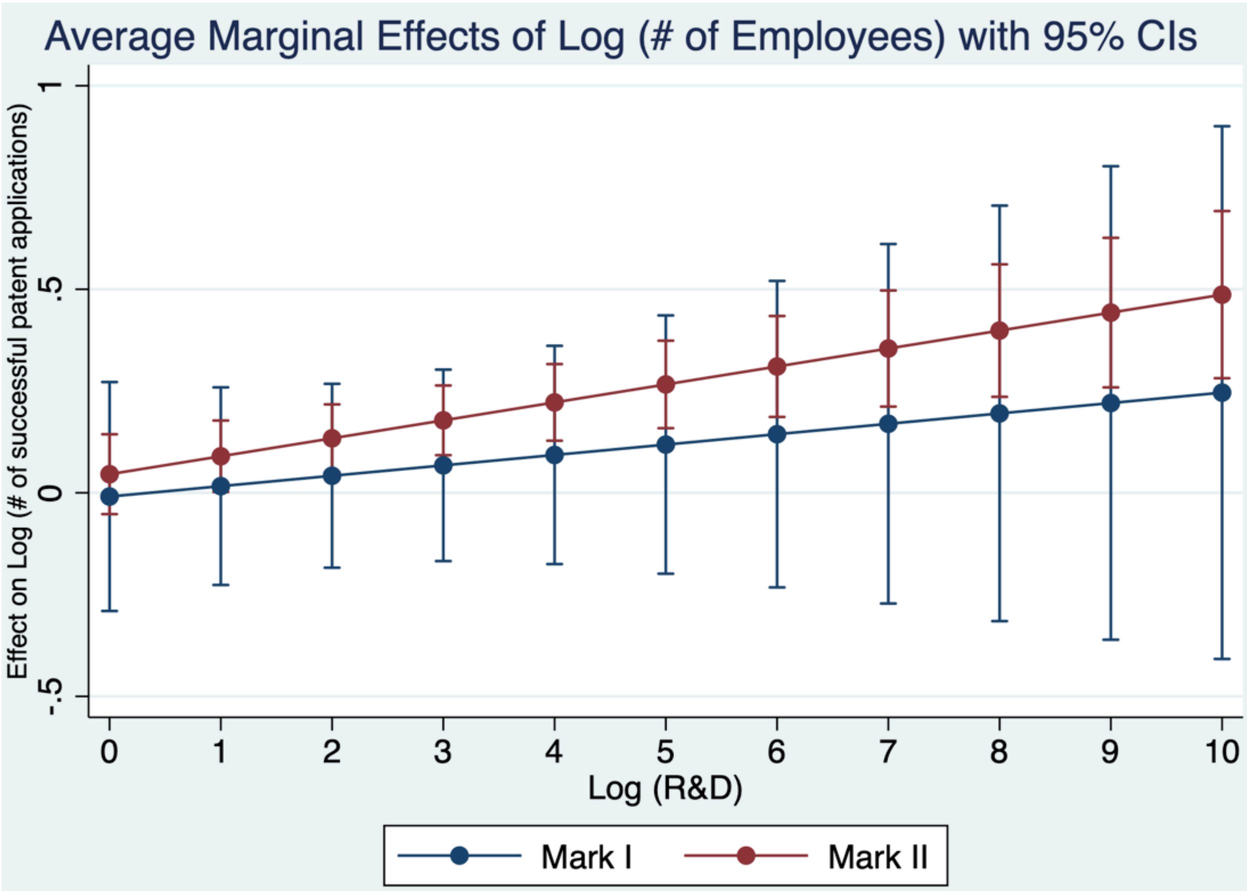
Model 1 & 2 observe the effect of R&D expenditure on innovation performance among the two subsamples with model 1 containing firms in Mark I industries and model 2 containing firms in Mark II industries (hypothesis 2). Model 3 & 4 observe the moderation effect of firm size on R&D efficiency for the two subsamples (hypothesis 3).

Figure 3: Conceptual framework of results



*0 P>0.1, *P<0.1, ** P<0.05, *** P<0.01*

Figure 4: Margins plot illustrating the moderation effect of firm size on the relationship between R&D expenditure and innovation output for Mark I and Mark II industries



The interaction is found to be significant for Mark II but not for Mark I industries. Therefore, the perceived positive moderation effect for Mark I may in fact be non-existent or negative. The intervals also indicate a possible negative relationship.

5. Robustness check

5.1. Lagged R&D expenditure

Even though a lagged R&D expenditure variable is not included in the main model, due to expected multicollinearity concerns, literature does suggest that R&D expenditures in previous years have an effect on innovation performance in the current year (Pakes et al., 1980; Kondo, 1999; Meliciani, 2000). Theoretically, this implies that it should be added to the model as control variable. Therefore, a robustness check is conducted where a 1-year lag R&D variable is included in the model. The results are shown in Table 11.

As expected, model 1 shows that the lagged variable is indeed positive and significant. This implies that an increase in R&D expenditure in the previous year increases the innovation performance in the current year. Nevertheless, the conclusions regarding the interaction terms observed for the hypotheses remain the same compared to the model without the lag (in Table 9). Thus, the effects of potential multicollinearity do not seem to influence the results significantly. However, it can be observed that adding the lagged variable slightly lowers the R-squared values and the amount of observations analysed as the first data year of all firms are not included. Therefore, the original model without lag seems to be a better fit for this specific analysis.

Table 11: OLS fixed effects regression with dependent variable Log 'number of successful patent applications' and lagged R&D expenditure

VARIABLES	(1) General	(2) H1	(3) H2	(4) H3
Log (R&D)	0.336***	0.305***	0.151	0.136
	(0.045)	(0.046)	(0.092)	(0.122)
Log (# of Employees)	0.176***	0.100**	0.159***	-0.062
	(0.044)	(0.050)	(0.044)	(0.158)
Log (R&D) x Log (# of Employees)		0.027**		0.035
		(0.012)		(0.041)
Mark II			-	-
Log (R&D) x Mark II			0.233**	0.208
			(0.101)	(0.132)
Log (# of Employees) x Mark II				0.150
				(0.168)
Log (R&D) x Log (# of Employees) x Mark II				-0.004
				(0.043)
Log ($R\&D_{t-1}$)	0.143***	0.127***	0.146***	0.128***
	(0.036)	(0.035)	(0.036)	(0.035)
Log (Age)	0.010	0.029	-0.017	-0.001
	(0.131)	(0.131)	(0.131)	(0.131)
Profit Margin	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	YES	YES	YES	YES
Constant	0.507	0.539*	0.542*	0.630*
	(0.322)	(0.322)	(0.320)	(0.325)
Observations	13,240	13,240	13,240	13,240
R-squared	0.102	0.103	0.103	0.106
Number of Firms	1,644	1,644	1,644	1,644

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2. Sales as indicator for firm size

As a robustness check, the amount of sales (USD deflated to constant price levels) are used as a measure for firm size, instead of the number of employees. This is done in order to validate the use of the chosen specification for firm size. Various literature justifies the use of sales to measure firm size in this specific context (Bound et al., 1984; Mansfield, 1986; Scherer, 1991). Table 12 shows the regression results.

With sales as indicator for firm size, the general model (model 1) shows a positive and significant effect of R&D expenditure and sales on innovation performance. Thus, similar to the original model, an increase in firm size also increases the number of successful patent applications. Model 2 shows a positive and significant interaction term between sales and R&D expenditure. Model 3 illustrates a positive and significant interaction for being in Mark II and R&D expenditure. Model 4 does not show a significant three-way interaction between these variables. Apart from the magnitudes, these results do not differ compared to the results in Table 9, which illustrates the main model where the number of employees is used as firm size indicator. Therefore, using the number of employees is considered a valid specification for firm size.

Table 12: OLS fixed effects regression with dependent variable Log 'number of successful patent applications' and 'Sales' as a measure of firm size

VARIABLES	(1) General	(2) H1	(3) H2	(4) H3
Log (R&D)	0.520***	0.331***	0.326***	0.160
	(0.040)	(0.069)	(0.097)	(0.314)
Log (Sales)	0.077**	-0.015	0.069**	0.060
	(0.032)	(0.042)	(0.032)	(0.146)
Log (R&D) x Log (Sales)		0.028***		0.019
		(0.010)		(0.039)
Mark II			-	-
Log (R&D) x Mark II			0.237**	0.194
			(0.104)	(0.322)
Log (Sales) x Mark II				-0.100
				(0.152)
Log (R&D) x Log (Sales) x Mark II				0.014
				(0.040)
Log (Age)	0.111	0.141	0.088	0.116
	(0.102)	(0.103)	(0.102)	(0.103)
Profit Margin	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	YES	YES	YES	YES
Constant	-0.183	0.291	-0.095	0.368
	(0.252)	(0.263)	(0.254)	(0.300)
Observations	14,884	14,884	14,884	14,884
R-squared	0.106	0.108	0.107	0.110
Number of Firms	1,644	1,644	1,644	1,644

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3. Poisson Fixed Effects model

Lastly, the same analysis is conducted using a Poisson fixed effects model. This robustness check is conducted, because it remains a challenge for literature to determine what type of estimation model best suits the R&D-patent relationship. Even though a Poisson model is highly restrictive, as it violates the assumption that the variance is equal to the mean because the dependent variable is severely overdispersed, it is still preferred over a Negative Binomial model for this specific research. Firstly, this is because a fixed effects estimator is used, which does not work well with a Negative Binomial model. A Negative Binomial model is namely based on a regression decomposition of the overdispersion parameter rather than on a regression decomposition of the mean (King, 1989; Cameron et al., 1990; Allison et al. 2002). Secondly, a Negative Binomial model still estimates a coefficient for the time-invariant variable *MarkII* when combined with fixed effects.

For this regression, it is necessary that the dependent variable, namely the number of successful patent applications, is a count variable (not in logarithmic form). Table 13 shows the regression results. Similar to the main OLS model, model 1 illustrates a positive and significant effect of R&D expenditure, the number of employees and profit margin on the number of successful patent applications. Contrary to the OLS regression, models 2, 3 & 4 do not show significant values regarding the interaction terms observed for the hypotheses. Therefore, the Poisson estimates do not indicate that either firm size or industry differences significantly moderate the effect of R&D expenditure on the number of successful patent applications. In addition, it does not indicate that the moderation effect of firm size differs per industry.

As a result, using a Poisson model opposed to an OLS model does affect the outcomes significantly. In accordance with the literature, this proves that choosing the best model remains a challenge when analysing the R&D-patent relationship (Bound et al., 1984; Wang et al., 1998; Wooldridge, 2010).

Table 13: Poisson fixed effects regression with dependent count variable number of 'successful patent applications' and number of employees as a measure of firm size

VARIABLES	(1) General	(2) H1	(3) H2	(4) H3
Log (R&D)	0.202**	0.203*	0.326**	0.316
	(0.096)	(0.117)	(0.131)	(0.206)
Log (# of Employees)	0.593***	0.594***	0.596***	0.233
	(0.131)	(0.130)	(0.131)	(0.308)
Log (R&D) x Log (# of Employees)		-0.000		0.027
		(0.019)		(0.044)
Mark II			-	-
Log (R&D) x Mark II			-0.135	-0.127
			(0.126)	(0.240)
Log (# of Employees) x Mark II				0.393
				(0.334)
Log (R&D) x Log (# of Employees) x (Mark II)				-0.029
				(0.048)
Log (Age)	-0.173	-0.174	-0.164	-0.166
	(0.167)	(0.171)	(0.169)	(0.171)
Profit Margin	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	YES	YES	YES	YES
Observations	14,884	14,884	14,884	14,884
Number of Firms	1,644	1,644	1,644	1,644

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Discussion

6.1. Research findings

6.1.1. H1: The moderating role of firm size

The moderating effect of firm size on the relationship between R&D expenditure and innovation performance is analysed. A significantly positive moderating affect is found. This is surprising, as most studies suggest that the number of patents per R&D dollar decreases with firm size (Panzar et al., 1981; Corsten, 1987; Acs et al., 1990; Cohen et al., 1996; Damanpour, 1996; Santoro et al., 2002; Herrera et al., 2013). Nevertheless, there are several potential explanations for hypothesis 1 to be rejected.

Firstly, most previous studies base their results on data from before the investigated time period of this research. Therefore, the findings in the current literature may be somewhat out-dated. Over the years, a transition may have taken place where firm size has become more important to R&D efficiency. As larger firms have more market share and power, they may be able to capture relatively higher returns to innovation due to their advantage in R&D in terms of appropriability. The lower fixed costs to launch an R&D effort and their ability to spread costs may not only contribute to higher levels of R&D but also higher levels of R&D efficiency compared to smaller firms (Schumpeter, 1942; Panzar et al., 1981; Cohen et al., 1996).

Secondly, Kim et al. (2009) argues that previous literature finding a negative effect of firm size on R&D efficiency is biased, because small firms have been under-reporting their R&D activities (more R&D expenditure than registered). In this dataset, under-reporting is assumed to not occur as much because all firms are publicly listed, thus strictly obliged to report all financials. As a result, the findings in this research may reflect a different outcome, namely a positive moderating effect of firm size on R&D efficiency.

A third explanation could be due to sample bias. Namely, all firms in the sample are relatively large (publicly listed). Tsai et al. (2005) finds that both the smallest and largest firms have highest R&D efficiency. As all firms in the sample are among the populations largest, this may provide reasoning as to why the firm size-R&D efficiency relationship may be positive. The smaller firms in this sample may not benefit as greatly from the small firm advantages, known to lead to higher R&D efficiency, such as flexibility, a stronger focus on advancing core technologies, a stronger focus on providing solutions to critical problems and a faster application of knowledge to the market (Corsten, 1987; Acs et al., 1990; Damanpour, 1996; Santoro et al., 2002; Herrera et al., 2013). Therefore, if the sample would include smaller firms such as start-ups or scale-ups, the overall relationship may be different.

It is important to note that this section discusses the overall effect of firm size on R&D efficiency for the entire sample without considering industry differences. This research believes that this effect varies when considering different industries. This is why hypothesis 2 and 3 investigate differences in the relationship between R&D expenditure and innovation performance for Mark I and Mark II industries and how the role of firm size may differ among these industries. Its results are discussed in the following.

6.1.2. H2: The moderating role of Mark I & Mark II

The moderating role of industry differences (Mark I, Mark II) on the relationship between R&D expenditure and innovation performance is analysed. A significantly positive moderating effect is found for Mark II industries compared to Mark I industries. This result is consistent with hypothesis 2, suggesting that being in a Mark II industry positively moderates the positive relationship between R&D expenditure and innovation performance, compared to being in a Mark I industry. Therefore, firms in Mark II industries resemble more efficient innovators, compared to firms in Mark I industries. Explanations for this result are discussed.

Previous literature suggests that the differences in industry technological regimes may affect the ability and importance of patenting, firms' incentives in R&D expenditure, and the degree to which R&D expenditure effects innovation performance. Most studies suggest that firms in Mark II contain higher R&D efficiencies, compared to firms in Mark I industries. This may be because firms in Mark II industries generally have better appropriability conditions, high cumulativeness, a high degree of technological opportunities and a high level of generic knowledge (Pavitt, 1984; Cohen et al., 1996; Breschi et al. 2000; Fontana et al., 2012). Especially high levels of appropriability and cumulativeness are found to have a positive effect on R&D efficiency. For example, if an industry contains high cumulativeness, the cost of the innovation tends to be lower, thus a one-dollar increase in R&D expenditure has a larger effect on innovation performance, compared to an industry with low cumulativeness of technical advances (Revilla et al., 2012). In turn, high appropriability increases the incentive to patent and innovate, which increases R&D expenditure because each dollar spent on R&D has a higher probability of turning into an innovation compared to an industry with low appropriability conditions (Levin, 1988).

Overall, even though no literature has specifically researched how firms in industries characterised by either Mark I or Mark II patterns differ in efficiencies regarding the effect of R&D expenditure on innovation performance, knowing that Mark II is characterised by high appropriability and cumulativeness as opposed to Mark I (Breschi et al. 2000) may be an explanation for why firms in Mark II industries are found to be more efficient innovators in this research.

6.1.3. H3: Differences in the moderating role of firm size for Mark I & Mark II

Essentially, hypothesis 3 is a combination of hypothesis 1 and 2. The differences in the moderation effect of firm size on the relationship between R&D expenditure and innovation performance among Mark I and Mark II industries are analysed. The hypothesis states, that the moderation effect of firm size on the positive relationship between R&D expenditure and innovation performance is positive and stronger for firms operating in Mark II, compared to Mark I industries. However, no significant three-way interaction is found, thus the hypothesis cannot be accepted nor rejected.

Nevertheless, the split sample analysis provides evidence that firm size significantly and positively moderates the effect of R&D expenditure on innovation performance in the Mark II industry. No significance is found for Mark I industries. Reason for this may be that the technological regime conditions in Mark II industries (e.g. high cumulativeness & high appropriability) favour larger firms. This suggests that not only larger firms innovate more according to Schumpeter Mark II (1942), they also innovate more efficiently in Mark II industries compared to smaller firms. The insignificance found in Mark I industries may suggest that firm size does not play an equally important role in contributing to R&D efficiency in these industries. Possibly, the Mark I technological regime characteristics (low appropriability, low cumulativeness, high technological opportunities, low generic knowledge and high specific knowledge) do not favour smaller or larger firms as much compared to how the technological regime conditions seem to favour larger firms in Mark II industries.

6.2. Implications

This research contains certain implications that could be of use for US R&D policy-makers and firms' managerial decision-making.

Firstly, R&D expenditure generally has a stronger social rate of returns compared to the private rate of return (Leyden & Link, 1991; David et al., 2000). This provides governments the incentive to endorse R&D efforts through subsidies or other supporting policies (Cin et al., 2014). However, the effectiveness of one additional dollar of R&D expenditure on innovation performance differs when considering firm and industry characteristics, making it challenging for governments to efficiently allocate R&D subsidies. Therefore, this research aims to provide more specific knowledge on what type of firms (regarding size and industry) use R&D most efficiently for innovation. Literature suggests that larger firms are more targeted and likely to use government R&D support, while smaller firms are significantly more able to produce innovations with R&D subsidies (Bérubé et al., 2009; Herrera et al., 2013). However, the results show that in Mark II industries, firm size positively moderates the effect of R&D expenditure on innovation performance. This seems to imply that it is justified for larger firms to obtain a larger portion of the allocation of R&D subsidies when in a Mark II industries, considering the fact that they use it more efficiently in conducting innovations. Subsequently, the same cannot be said for firms in Mark I industries. Here, the results do not find evidence that firm size is positively (or negatively) related to R&D efficiency. Thus, it cannot be neglected that smaller firms may well be more efficient in Mark I industries. As a result, it may not be valid that most US R&D subsidies are provided to larger firms in Mark I industries as well. Therefore, it may be interesting for future research to examine the trend more closely for Mark I industries as the result could impact government legislation. With this knowledge, the government may consider providing R&D subsidies or tax credits to either larger or smaller sized firms depending on the industry.

Apart from policy implications, this research also provides knowledge that may influence firms' managerial decision-making with regard to R&D expenditure. According to a firm's size and industry characteristics, this research sheds light on the additional number of successful patent applications firms obtain from spending more on R&D compared to the rest of the publically listed firms in the sample. As a result, firms could adjust their R&D investment strategy according to their R&D efficiency. For example, a larger firm operating in a Mark II industry may consider spending proportionately more on R&D, relative to smaller firms in the same industry. In addition, Mark II technological regime elements such as high cumulativeness enhance R&D efficiency as the cost of innovation tends to be lower (Ettlie et al., 1984; Revilla et al., 2012). Therefore, firms in industries with high cumulativeness of technical advances (Mark II) may consider innovating more along specific trajectories in the future by focussing more on gradual improvements of previous innovation. With data on the separate technological regime elements, future research could investigate which elements contribute most to R&D efficiency. With this information, firms would then be able to alter their investment strategy according the characteristics it encounters (e.g. spend relatively more on R&D if appropriability conditions are very high).

6.3. Limitations & suggestions for further research

Several limitations of this study are identified and further research may amplify the findings of this study. Firstly, data is collected solely from US publically listed firms. Thus, the research findings are not representative for the whole population of US firms. Future research could extend by including data from a larger population also consisting of (smaller) firms, such as start-ups or scale-ups to obtain a more generalizable result.

Secondly, even though using the number of successful patent applications as key performance indicator for innovation performance is widely accepted and used in the literature, this choice of measurement does carry its flaws (Fagerberg, 2013). First, many innovations are not patented or patentable (some use a different protection mechanism), thus are not taken into consideration in this research. Second, patents are awarded to inventions and not innovations. Even though the number of 'granted' patents (successful applications) are used, many inventions still do not commercialize and do not become innovations. In addition, patents are not regarded as an essential incentive to innovate in all industries. Therefore, future research may experiment by using an alternative indicator for innovation performance, such as the percentage of sales due to new products or services.

Third, no distinction is made regarding the type of innovations. If this data becomes more available, future research could be able to analyse how the effect is different for incremental and radical innovations.

Fourth, the dependent variable R&D expenditure may have its restrictions. Despite publically listed firms' obligation to report all financials, R&D expenditure may still be subject to biases caused by financial under-reporting. Many R&D activities take place outside of the formal R&D operations, especially with smaller firms that do not have an R&D department. This may lead to an underestimation of R&D expenditure for smaller firms (Cohen et al., 1989; Kim et al., 2009). Therefore, future research could consider using the number of inventors per firm as R&D input (Kim et al., 2009). In addition, literature and the robust analysis show that R&D expenditures in previous years have an effect on the number of successful patent applications. However, this tends to differ per industry. For example, it can take up to 12 years for R&D expenditure to become translated into a patent in pharmaceutical industries (Hashimoto et al., 2008). Future research could consider observing the relationship among different industries by adding lagged R&D variables suitable for each specific industry. However, multicollinearity issues may occur. As an alternative, future research may consider averaging the R&D expenditure from the past 3 years (depending on the industry) and using this as independent variable. This, however, may lead to difficulties regarding interpretation. Lastly, it may also be interesting to analyse whether a moderation effect takes place between firm size and a lagged R&D expenditure and how this moderation with lags may differ between industries.

Fifth, the 47 NAICS industries are aggregated into two classes, namely Mark I industries and Mark II industries. This classification is based on the classification of industries in technological categories from previous research (Breschi et al., 2000; Fontana et al., 2012). Although theoretically sound, in practice some great assumptions have been made in order to obtain such a Mark I and Mark II classification. With available (survey) data on the industry technological regime elements (appropriability, cumulativeness, technological opportunities and knowledge base) similar to Breschi et al. (2000), future research could create a more thorough classification of Mark I and Mark II. As a result, future studies may investigate which elements of the technological regime contribute most to R&D efficiency, which could be valuable information for managerial decision-making and the efficient allocation of R&D subsidies.

Sixth, the full sample analysis shows an insignificant triple interaction, suggesting that the moderation effect of firm size on R&D efficiency does not significantly differ among industries. This type of analysis does not allow for analysing separate effects within an industry, making it challenging to explain why the effect is insignificant. Therefore, a split sample is also analysed in this research. The split sample finds a significant positive moderation effect of firm size on R&D efficiency for Mark II industries but no significant effect for Mark I industries, suggesting that the moderating effect of firm size on R&D efficiency tends to differ per industry. However, a split sample analysis carries the disadvantage that only part of the observations are analysed at once, often resulting in a loss of statistical power. For this research, Mark I contains 2643 observations (254 firms), whilst Mark II contains 12241 observations (1390 firms). Consequentially, the R-square value of the Mark I sample is 0.05 and for Mark II 0.13 (Table 10). This substantially lower amount of observations in Mark I may possibly contribute to the insignificance of its moderation effect. With more observations, especially for Mark I, the accuracy of the results may improve, as the statistical power is likely enhanced.

Seventh, the R-square values indicate that approximately 89% of the main model's variation is explained by other omitted variables (Table 9). Future research may include additional control variables in order to obtain a better approximation of the results. Examples of additional variables that may affect R&D efficiency could potentially be the location of the firm, collaborations or partnerships, or the average age of employees.

Lastly, the data used is unbalanced with gaps. Partly for this reason, a time-demeaning fixed effects model controlling for within variation is applied with robust standard errors and clustering. Despite this, there are still concerns of attrition bias where the dropouts influence the statistical power of the study. Thus, a more balanced dataset without gaps could enhance the accuracy of the estimations. In turn, this may allow for the experimentation of applying different models that can estimate time-invariant coefficients. Section 5.3. finds different (insignificant) outcomes for a Poisson fixed effects model. Even though several arguments are given as to why a Poisson or Negative Binomial model are inferior to the OLS, literature does not provide evidence leading to full certainty that this is indeed the best application.

7. Conclusion

In search of what type of firms are most efficient innovators, it is important to investigate how the relationship between R&D expenditure and innovation performance (R&D efficiency) is influenced by firm size and its industry. Unprecedentedly, this research aims to find out whether and why in some industries, larger firms may be more efficient innovators and in other industries, smaller firms may be more efficient innovators. No study has yet observed the moderating effect of firm size and industries on the relationship between R&D expenditure and innovation performance, and how firm size may affect the relationship differently among industries. Therefore, this study contributes to the existing literature with respect to the following conclusions.

Firstly, the majority of studies find that, overall, smaller firms tend to be more R&D efficient compared to larger firms, suggesting that firm size has a negative effect on R&D efficiency. However, for a set of US publically listed firms, this research finds evidence that, in general, firm size positively moderates the positive relationship between R&D expenditure and innovation performance.

Apart from firm size, previous literature finds R&D efficiencies to differ among industries. Literature suggests that differences in industry technological regimes may affect the ability and importance of patenting, firms' incentives in R&D expenditure, and the degree to which R&D

expenditure effects innovation performance. Most studies find that firms operating in Mark II industries contain higher R&D efficiencies compared to firms operating in Mark I industries[3]. The results of this study support this, as it finds that being in a Mark II industry positively moderates the positive relationship between R&D expenditure and innovation performance, compared to being in a Mark I industry.

Third, previous studies indicate that the effect of firm size on R&D efficiency may differ depending on the industry. Their findings suggest that firm size has a positive and stronger moderating effect on the positive relationship between R&D expenditure and innovation performance for firms operating in Mark II compared to Mark I industries. The result of the triple interaction term in this study does not find significant evidence to support this. Nonetheless, a split sample analysis does show that firm size positively and significantly moderates the effect of R&D expenditure on innovation performance for the sample of firms in Mark II industries, but not necessarily for firms in Mark I industries. Thus, an increase in firm size leads to higher R&D efficiency for firms in Mark II industries, whilst the same or the contrary cannot be said for firms in Mark I industries. Due to insignificance in Mark I, it cannot remain unmentioned that firm size may have no effect or even a negative effect on R&D efficiency in these industries.

To conclude, this research identifies that firm size and industry differences, significantly affect the efficiency of firms in transforming R&D expenditure into innovations. It also indicates that the relationship between firm size and R&D efficiency is likely to differ depending on the industry and its varying technological regime characteristics.

[3] Schumpeter Mark 1 industry technological regime characteristics: Low appropriability, low cumulativeness, high technological opportunities, low generic knowledge, high specific knowledge. Schumpeter Mark I industry technological regime characteristics: High appropriability, high cumulativeness, low/high technological opportunities, high generic knowledge, low specific knowledge.

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9. Appendix

Table 3: North American Industry Classification System (NAICS) description

HJT Technology category	Industry patent mode HJT Technology Categories	NAICS digit category	2017 NAICS Code	2017 NAICS Title	Number of observations	Number of firms
		NAICS-2	11	Agriculture, Forestry, Fishing and Hunting[T]		
Drugs & Medical	3	NAICS-3	111	Crop Production[T]	34	5
		NAICS-2	21	Mining, Quarrying, and Oil and Gas Extraction[T]		
Chemical	1	NAICS-3	211	Oil and Gas Extraction[T]	26	3
Chemical	1	NAICS-3	212	Mining (except Oil and Gas)[T]	37	4
Others	6	NAICS-3	213	Support Activities for Mining[T]	98	7
		NAICS-2	23	Construction[T]		
Others	6	NAICS-3	237	Heavy and Civil Engineering Construction[T]	9	1
		NAICS-2	31-33	Manufacturing[T]		
Others	6	NAICS-3	311	Food Manufacturing[T]	227	22
Others	6	NAICS-3	312	Beverage and Tobacco Product Manufacturing[T]	39	3
Others	6	NAICS-3	313	Textile Mills[T]	56	5
Others	6	NAICS-3	314	Textile Product Mills[T]	11	2
Others	6	NAICS-3	315	Apparel Manufacturing[T]	11	2
Others	6	NAICS-3	316	Leather and Allied Product Manufacturing[T]	20	3
Others	6	NAICS-3	321	Wood Product Manufacturing[T]	22	2
Others	6	NAICS-3	322	Paper Manufacturing[T]	220	21
Others	6	NAICS-3	323	Printing and Related Support Activities[T]	36	4
Chemical	1	NAICS-3	324	Petroleum and Coal Products Manufacturing[T]	210	22
Chemical	1	NAICS-3	325	Chemical Manufacturing[T]	2808	318
Mechanical	5	NAICS-3	326	Plastics and Rubber Products Manufacturing[T]	256	28
Chemical	1	NAICS-3	327	Nonmetallic Mineral Product Manufacturing[T]	160	14
Mechanical	5	NAICS-3	331	Primary Metal Manufacturing[T]	196	23
Mechanical	5	NAICS-3	332	Fabricated Metal Product Manufacturing[T]	399	31
Electronics	4	NAICS-3	333	Machinery Manufacturing[T]	1626	164
Computers & communications	2	NAICS-3	334	Computer and Electronic Product Manufacturing[T]	4282	489
Computers & communications	2	NAICS-3	335	Electrical Equipment, Appliance, and Component Manufacturing[T]	594	57
Mechanical	5	NAICS-3	336	Transportation Equipment Manufacturing[T]	793	74
Others	6	NAICS-3	337	Furniture and Related Product Manufacturing[T]	132	10
Drugs & Medical	3	NAICS-3	339	Miscellaneous Manufacturing[T]	861	102
		NAICS-2	42	Wholesale Trade[T]		
Others	6	NAICS-3	423	Merchant Wholesalers, Durable Goods	34	4
Drugs & Medical	3	NAICS-3	424	Merchant Wholesalers, Nondurable Goods	32	4
		NAICS-2	44-45	Retail Trade[T]		
Others	6	NAICS-3	454	Nonstore Retailers	16	2
		NAICS-2	51	Information[T]		
Computers & communications	2	NAICS-3	511	Publishing Industries (except Internet, incl. software publishing)[T]	635	87
Computers & communications	2	NAICS-3	512	Motion Picture and Sound Recording Industries[T]	8	1
Computers & communications	2	NAICS-3	515	Broadcasting (except Internet)[T]	6	1
Computers & communications	2	NAICS-3	517	Telecommunications[T]	186	25
Computers & communications	2	NAICS-3	518	Data Processing, Hosting, and Related Services[T]	53	5
Computers & communications	2	NAICS-3	519	Other Information Services[T]	47	7
		NAICS-2	53	Real Estate and Rental and Leasing[T]		
Chemical	1	NAICS-3	531	Real Estate (incl. Timber Real Estate)[T]	13	2
Others	6	NAICS-3	532	Rental and Leasing Services[T]	13	2
Computers & communications	2	NAICS-3	533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)[T]	61	8
		NAICS-2	54	Professional, Scientific, and Technical Services[T]		
Computers & communications	2	NAICS-3	541	Professional, Scientific, and Technical Services[T]	399	54
		NAICS-2	56	Administrative and Support and Waste Management and Remediation Services[T]		
Others	6	NAICS-3	561	Administrative and Support Services[T]	25	4
	3	NAICS-3	562	Waste Management and Remediation Services[T]	6	1
		NAICS-2	62	Health Care and Social Assistance[T]		
	3	NAICS-3	621	Ambulatory Health Care Services[T]	37	4
		NAICS-2	71	Arts, Entertainment, and Recreation[T]		
Others	6	NAICS-3	713	Amusement, Gambling, and Recreation Industries[T]	26	3
		NAICS-2	72	Accommodation and Food Services[T]		
Electronics	4	NAICS-3	721	Accommodation[T]	3	1
	6	NAICS-3	722	Food Services and Drinking Places[T]	4	1
		NAICS-2	81	Other Services (except Public Administration)[T]		
Electronics	4	NAICS-3	812	Personal and Laundry Services[T]	7	1
		NAICS-2	99	Unclassified[T]		
Electronics	4	NAICS-3	999	Unclassified[T]	110	11
		Total	Average		14884	1644

Table 3: Continued

Chemical	1	**Total**	**Average**		3254	363
Computers & communications	2	**Total**	**Average**		6271	734
Drugs & Medical	3	**Total**	**Average**		970	116
Electronics	4	**Total**	**Average**		1746	177
Mechanical	5	**Total**	**Average**		1644	156
Others	6	**Total**	**Average**		999	98

T = trilateral agreement (United States, Canada, and Mexico)

Table 8: Different models often used to estimate the R&D-Patent relationship

MODEL	(OLS)	(Poisson)	(Negative Binomial)
VARIABLES	D.V. = Log (#Successful Patent applications)	D.V. = # Successful Patent applications	D.V. = # Successful Patent applications
Log (R&D)	0.548***	0.211**	0.184***
	(0.026)	(0.095)	(0.011)
Log (Age)	0.025	-0.176	-0.005
	(0.044)	(0.165)	(0.022)
Profit Margin	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)
Log (# of Employees)	0.149***	0.581***	0.138***
	(0.021)	(0.127)	(0.010)
Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
Constant	0.059	1.875***	-0.900***
	(0.154)	(0.520)	(0.081)
Observations	14,884	14,884	14,884
Number of Firms	1,644	1,644	1,644

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: VIF values on the left including lagged independent variable ($R\&Dexp_{t-1}$) and on the right excluding.

	Including lagged R&D expenditure		**Excluding lagged R&D expenditure**	
	VIF	**1/VIF**	**VIF**	**1/VIF**
Log (R&D)	38.53	0.025951	2.41	0.414518
Log (R&D t-1)	38.26	0.026140	-	-
Log (Age)	1.38	0.723438	1.39	0.718108
Profit Margin	1.00	0.996935	1.00	0.996894
Log (# of Employees)	2.89	0.346394	2.87	0.348483
Year				
1992	-	-	1.97	0.508274
1993	1.96	0.509007	2.07	0.483909
1994	2.02	0.495344	2.08	0.481035
1995	2.07	0.483011	2.15	0.465917
1996	2.17	0.461207	2.23	0.447637
1997	2.21	0.452352	2.28	0.438745
1998	2.22	0.449944	2.35	0.425733
1999	2.23	0.449032	2.33	0.429761
2000	2.25	0.443461	2.32	0.431133
2001	2.26	0.442438	2.42	0.413840
2002	2.36	0.424575	2.43	0.411104
2003	2.40	0.417509	2.46	0.406821
2004	2.45	0.408598	2.47	0.404490
2005	2.42	0.412643	2.44	0.409592
2006	2.39	0.417720	2.39	0.418980
2007	2.29	0.437027	2.29	0.436939
2008	2.21	0.452487	2.19	0.457550
2009	2.03	0.493662	1.99	0.502194
2010	1.79	0.558549	1.77	0.565699
Mean VIF	5.30		2.19	

Table 15: OLS fixed effects regression with dependent variable Log 'number of successful patent applications' and independent variable 'nextwave' to test for attrition bias

VARIABLES	(1) General
Nextwave	0.142***
	(0.027)
Log (R&D)	0.459***
	(0.043)
Log (# of Employees)	0.165***
	(0.041)
Log (Age)	0.130
	(0.102)
Profit Margin	0.000***
	(0.000)
Year Fixed Effects	YES
Constant	0.199
	(0.245)
Observations	14,884
Number of Firms	1,644
R-squared	0.110

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$